Silvo Dajčman[1]

LONG MEMORY IN RETURNS OF SLOVENIAN STOCK MARKET INDEX AND MAJOR STOCKS LISTED ON LJUBLJANA STOCK EXCHANGE

This study investigates whether the long memory in the time series of stocks and stock index returns. Different methods of calculating long memory parameters are applied to prove if the estimates are sensitive to the method chosen. We found that Slovenian aggregated stock market returns as well as majority of the individual stocks listed on Slovenian stock market do exhibit long memory. Different methods of estimating the long memory parameter yielded similar conclusions regarding long memory evidence.

Keywords: *stock market; long memory; efficient-market hypothesis.*
JEL classification: G14, G15.

Сільво Дайчман

ДОВГОСТРОКОВА ПАМ'ЯТЬ РЕНТАБЕЛЬНОСТІ СЛОВЕНСЬКОГО БІРЖОВОГО ІНДЕКСУ І ОСНОВНИХ АКЦІЙ НА ЛЮБЛЯНСЬКОЙ БІРЖІ

У статті досліджено довгострокову пам'ять у часових рядах рентабельності акцій і біржових індексів на словенській біржі. Застосовано різні методи розрахунку параметрів довгострокової пам'яті для виявлення чутливості показників до вибраного методу. Виявлено, що узагальнені біржові доходи, а також більшість індивідуальних акцій на словенській біржі проявляють довгострокову пам'ять. Різні методи оцінювання параметру довгострокової пам'яті дали ті ж результати відносно довгострокової пам'яті.

Ключові слова: *біржа; довгострокова пам'ять; гіпотеза ефективного ринку.*
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Сильво Дайчман

ДОЛГОСРОЧНАЯ ПАМЯТЬ РЕНТАБЕЛЬНОСТИ СЛОВЕНСКОГО БИРЖЕВОГО ИНДЕКСА И ОСНОВНЫХ АКЦИЙ НА ЛЮБЛЯНСКОЙ БИРЖЕ

В статье исследуется долгосрочная память во временных рядах рентабельности акций и биржевых индексов на словенской бирже. Применены различные методы подсчета параметров долгосрочной памяти для обнаружения чувствительности показателей к выбранному методу. Обнаружено, что обобщенные биржевые доходы, а также большинство индивидуальных акций на словенской бирже проявляют долгосрочную память. Различные методы оценки параметра долгосрочной памяти дали те же результаты относительно долгосрочной памяти.

Ключевые слова: *биржа; долгосрочная память; гипотеза эффективного рынка.*

Introduction. Long memory (or long-term dependence or fractal dimension processes; see Mandelbrot, 1977) describes the correlation structure of a series for long lags. If a series exhibits long memory (or the "biased random walk"), there is persistent temporal dependence even between distant observations (Barkoulas et al., 2000). The presence of long-memory components 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 deci-

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sions would become extremely sensitive to the investment horizon if stock returns were long-range dependent (Lo and MacKinlay, 2001). Furthermore, according to LeRoy (1989), CAPM and 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 series dynamics (Barkoulas and Baum, 1996). According to Fama (1970), financial markets can only be called efficient if 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. In most empirical literature, the random walk behavior of security prices is used as a basis to test for the weak form of stock market efficiency (Dima and Milos, 2009).

Due to their flexibility, ARFIMA (Autoregressive Fractionally Integrated Moving Average) models have often been used to model stock returns and their volatilities. Evidence on the long memory in stock market returns and their volatilities is mixed. Studies, supportive of long memory in stock market returns or their volatility include: Ding et al. (1993) for the S&P500 index in the period 1928–1992, Lobato and Savin (1998) for the S&P500 in the period 1962–1994 and Ray and Tsay (2000) for the companies listed on the S&P500 index for the period 1962–1995. Barkoulas et al. (2000) found significant and robust evidence of positive long-term persistence for the stocks traded on the Athens stock exchange for the period 1981–1990. Assaf and Cavalcante (2005) provide empirical evidence of the long-range dependence in the returns and volatility of Brazilian stock market in the period from the start of 1994 until May 2002. Supportive evidence of long memory is also provided by Chan and Feng (2008) for DJI, S&P500, FTSE, DAX and NIKKEI (for different time periods), Bilel and Nadhem (2009) for G7 countries stock indices for high frequency data between 2003–2004 and Mariani et al. (2010) for international stock indices.

Mixed results were obtained by Henry (2002), after investigating 9 developed stock market indices for the period 1982–1998. He only found strong evidence for long memory in the South Korean returns and some evidence of long memory in German, Japanese and Taiwanese returns. Tolvi (2003) having investigated the stock market indices of 16 OECD countries for the period 1960–1999, only found evidence of long memory in stock indices returns for 3 smaller stock markets: Finland, Denmark and Ireland. Jagric et al. (2005) found mixed evidence of long memory presence in the stock indices of 6 Central and Eastern European (CEE) countries for the period 1991–2004: strong long-range dependence was identified in the returns of Czech, Hungarian, Russian and Slovenian stock markets, whereas there was weak or no long-range dependence in the returns of Slovakian and Polish stock markets. Another study investigating the fractal structure of the CEE stock market returns was by Kasman et al. (2009a). Their results point to the existence of long memory in 5 of the 8 studied markets.

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), which 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 7 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 exists 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 index returns and individual stocks listed on Slovenian stock market 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: Kwiatkowski-Phillips-Schmidt-Shin (KPSS) (1992) test, the method of Geweke and Porter-Hudak (GPH), and the Robinson's (1995) method of local Whittle approximation. As the fractal structure of individual stock returns may be masked in the fractal structure of a stock index, which incorporates the stock, the fractal structure of individual stock returns included in stock indices can also be calculated. The results of the paper are also informative of the weak efficiency hypothesis of the stock market and individual shares at the stock market.

The long memory property of time series. 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 $\omega(\gamma_s)$ 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 long memory parameter d, called also a fractional integration parameter, arises from the generalization of the Box-Jenkins ARIMA(p,d,q) models from integer to non-integer values of the integration parameter d and was introduced by Granger and Joyeux (1980) and Hosking (1981). A general class of fractional processes ARIMA(p,d,q) is described as (Sadique and Silvapulle, 2001):

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

where $(1-B)^d$ is the fractional differencing operator, innovation is a Gaussian white noise $\varepsilon_t \sim IID(0,\sigma^2)$. 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. d, however, can also take fractional values, in the interval (–0.5,0.5) and is therefore called a fractional integration parameter varying in the interval.

It may be shown that for or $-0.5 < d < 0.5$ 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 $-0.5 < d < 0$. 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 Surinach 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.

Methodology. Simulation studies (Taqqu and Teverovsky, 1996; Rea et al., 2007; Boutahar et al., 2005) show that different methods for estimating the fractional integration parameter can lead to different conclusions regarding fractal structure in 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 time series (Taqqu and Teverovsky, 1996).

In our study, the fractal structure parameter d is calculated by these methods: i) Kwiatowski-Phillips-Schmidt-Shin (KPSS) (1992) test, ii) the GPH estimator and iii) Robinson's (1995) method of local Whittle approximation.

1. KPSS test in combination with unit root tests. Lee and Schmidt (1996) proposed test of Kwiatkowski-Phillips-Schmidt-Shin 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 3 components, a deterministic time trend (ct) a random walk (r_t) and a stationary error (ε_t) (Kwiatkowski et al., 1992):

$$X_t = r_t + ct + \varepsilon_t, \tag{4}$$

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 statistics is computed as:

$$KPSS = \sum_{t=1}^{T} \frac{(s(t))^2}{s_{nw}^2 T^2}, \tag{5}$$

where $s(t) = e_1 + \ldots + e_t$, 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), 2 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 rejection of the null hypothesis of the ADF, PP and KPSS tests 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).

2. Method of Geweke and Porter-Hudak (GPH). The GPH estimator is based on the low-frequency spectral behavior of a series. As a fractionally integrated process with $0 < d < 0.5$ has a very large portion of its variance explained by very low frequency components, the periodogram should indicate an inverse relationship between the level of the periodogram and the frequency at which the level is evaluated. The GPH estimator captures this relationship through a simple OLS regression, in logs, for the level of the periodogram on the frequencies. More specifically, the estimation of parameter d is based on a linear regression of the log-periodogram function:

$$\ln P_x(\lambda_s) = c - d\ln\left(4(\sin^2(\lambda_s)\right) + \varepsilon(\lambda_s), \tag{6}$$

where $P_x(\lambda_s) = |\omega_x(\lambda_s)|^2$ is a periodogram of the data computed at the harmonic Fourier frequencies around zero, $\lambda_s = 2\pi s / N$ ($s = 1, ..., m < N / 2$, N is a number of observations), c is a constant and ε a residual of regression estimation. The discrete Fourier transformation is defined as:

$$\omega_x(\lambda_s) = (2\pi N)^{-\frac{1}{2}} \sum_{t=1}^{N} X_t e^{it\lambda_s}. \tag{7}$$

The GPH estimator of d is obtained by regressing the log-periodogram on log frequency for the first m Fourier frequencies. The choice of m is crucial in practice, since it determines the bias, variance and mean squared error of the estimator. According to Cheung and Lai (1993) a large number of m will contaminate the estimate of d, while too few will produce imprecise estimates of d. Geweke and Porter-Hudak (1983) suggested $m = N^{0.5}$, but in empirical analysis, parameter d is estimated for more choices of m (very common choices are also $m = N^{0.45}$ and $m = N^{0.55}$ (Elder et al., 2006). Geweke and Porter-Hudak (1983) show that for $m = N^{\mu}$ ($0 < \mu < 1$) the GPH estimator of d is obtained by ordinary least squares and hypothesis testing concerning the value of d can be based on the t-statistics of the slope coefficient. The theoretical asymptotic variance of ε is equal to $\pi^2 / 6N$ and can be imposed in the construction of t-statistics for d to raise the estimation efficiency. The method is robust only for $|d| < 0.5$ (Charfeddine and Guegan, 2007).

3. The local Whittle estimator of Robinson. To mitigate the bias in the GPH estimator, 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 Kunsch (1987):

$$Q_m(G,H) = \frac{1}{m}\sum_{s=1}^{m}\left[\log(G\lambda_s^{1-2H}) + \frac{\lambda_s^{2H-1}}{G}P_x(\lambda_s)\right], \tag{8}$$

where $\lambda_s = 2\pi s / N$ ($s = 1, 2, ..., N,$ and $G \in (0,\infty)$. The estimator depends on the choice of bandwidth, m, which is generally chosen in the range $N^{0.5} \le m \le N^{0.8}$ (see

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:

$$\hat{H} = \operatorname{argmin} R(H), \quad H \in [\Delta_1, \Delta_2], \tag{9}$$

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 $d = H - 0.5$. Robinson (1995) demonstrated that the local Whittle estimator is asymptotically more efficient than the GPH estimator.

Data and empirical results. Stock (stock index) returns are calculated as the differences of logarithmic daily closing prices of stocks (or stock indices) ($\ln(P_t) - \ln(P_{t-1})$, where P is a closing price). We included all stock listed on the main stock index (LJSEX) and were regularly traded in the stock exchange during the whole observed period. The first date of observation is April 4, 1996. The data of stock (stock indices) prices were obtained from the web pages of the Ljubljana stock exchange.

Table 1 presents some descriptive statistics of the data. The data appear to be extremely non-normal. The data reveals a high degree of excess kurtosis and the Jarque-Bera test rejects the hypothesis of normally distributed returns for all the stocks as well as stock indices.

The 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 (Table 2). The null hypothesis of the KPSS test (i.e. the time series is stationary) is rejected for some stocks: Aerodrom Ljubljana, Intereuropa, Lasko, Luka Koper and also for the stock index LJSEX, meaning that these time series are fractionally integrated.

The null of the GPH, i.e. that the time series is stationary ($H_0 : d = 0$), was tested against the alternative of long memory in a time series ($H_1 : d \neq 0$). In order to check the robustness of the GPH results, the parameter d was estimated at multiple frequencies: $m = N^{0.45}$, $m = N^{0.5}$, $m = N^{0.55}$, $m = N^{0.7}$ and $m = N^{0.8}$. As Table 3 demonstrates, there is evidence that Slovenian stock market exhibits fractional dynamics with long-memory features. However, the results are sensitive to the number of frequencies included in the calculation of the GPH estimator. When only lower frequencies $[N^{0.45}] \leq m \leq [N^{0.55}]$ are included in the GPH estimator, the null of an $I(0)$ process can be rejected for Aerodrom Ljubljana, Gorenje, Intereuropa, Lasko, Luka Koper, Petrol, Sava and the LJSEX index. For all the frequencies of the periodogram, Gorenje, Intereuropa and the LJSEX index exhibited long memory in returns.

Robinson's (1995) local Whittle estimator of the fractional differencing parameter d depends on the choice of bandwidth, m, which is generally chosen in the range $N^{0.5} \leq m \leq N^{0.8}$ (Baillie and Kapetanios, 2009). We chose bandwidths with the sizes $m = [N^{0.5}]$, $m = [N^{0.7}]$ and $m = [N^{0.8}]$. The results are displayed in Table 4.

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

Stock /stock index	Period of observation	Number of obser.	Min	Max	Mean	Std. deviation	Skewness	Kurtosis	Jarque-Bera statistics
Aerodrom Ljubljana	8.10.1997-20.7.2010	3,190	-0.1557	0.1656	0.0001783	0.01959	-0.0530	9.8111	6,167.71***
Gorenje	2.6.1998-20.7.2010	3,030	-0.0955	0.1045	0.0001288	0.01608	0.1178	7.4480	2,504.87***
Intereuropa	12.1.1998-20.7.2010	3,128	-0.1016	0.1542	-0.000349	0.01634	0.3116	12.1472	10,955.89***
Krka	10.2.1997-20.7.2010	3,320	-0.2679	0.1984	0.000445	0.0179	-0.3787	38.3947	17,3381,37***
Lasko	1.2.2000-20.7.2010	2,607	-0.1504	0.1263	-0.0001871	0.01995	-0.1596	9.4116	4,476.48***
Luka Koper	20.11.1996-20.7.2010	3,408	-0.0965	0.1281	0.00006687	0.01724	-0.0279	7.9459	3,474.08***
Mercator	4.4.1996-20.7.2010	3,563	-0.1751	0.1554	0.0005507	0.01883	0.2253	13.9417	17,803,66***
Petrol	5.5.1997-20.7.2010	3,300	-0.102	0.1328	0.0002867	0.01623	0.3266	11.0921	9,062.37***
Sava	6.1.2000-20.7.2010	2,625	-0.1274	0.1535	0.0002616	0.0181	0.0096	9.8419	5,120.06***
LJSEX (index)	4.4.1996-20.7.2010	3,564	-0.1161	0.1893	0.0002782	0.01183	0.3543	34.1558	144,220.93***

Notes: Jarque-Bera statistics: *** indicate that the null hypothesis (of normal distribution) is rejected at the 1% significance.

Table 2. **Descriptive statistics for returns series of stocks listed at Ljubljana stock exchange and its representative stock index**

	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)
Lasko	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: KPSS and PP tests are performed for two models: for the 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 parenthesis under the statistics. For ADF test, two models are applied: the model with a constant and the model with a constant plus trend; number of lags to be included (L) 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 in the testing model is significant, this is denoted in the table.

Table 3. **The results of the GPH test**

	m = [$N^{0.45}$]	m = [$N^{0.5}$]	m = [$N^{0.55}$]	m = [$N^{0.7}$]	m = [$N^{0.8}$]
Aerodrom Ljubljana	0.4072*** (0.0138)	0.3452*** (0.0062)	0.3440*** (5.7761e-004)	0.0178 (0.6875)	-0.0408 (0.1367)
Gorenje	0.1813* (0.0872)	0.2843*** (0.0029)	0.2200*** (0.0036)	0.0990** (0.0129)	0.0760*** (0.0038)
Intereuropa	0.3015** (0.0192)	0.3042*** (0.0012)	0.3120*** (1.9782e-004)	0.0998** (0.0194)	0.0454* (0.0982)
Krka	0.2024 (0.1267)	0.0880 (0.3756)	0.1188 (0.1251)	0.0487 (0.2181)	-0.0188 (0.4849)
Lasko	0.3908*** (1.5016e-004)	0.4630*** (4.0952e-004)	0.3583*** (6.1416e-004)	-0.0144 (0.7515)	-0.0428 (0.1677)
Luka Koper	0.3871*** (0.0061)	0.2904*** (0.0080)	0.2509*** (0.0024)	0.0482 (0.2509)	0.0240 (0.3828)
Mercator	0.1894* (0.0442)	0.1001 (0.1508)	0.1091* (0.0624)	0.0553 (0.1437)	-0.0456* (0.0763)
Petrol	0.2310* (0.0574)	0.1819** (0.0415)	0.1871*** (0.0093)	0.0784** (0.0394)	0.0071 (0.7741)
Sava	0.1743 (0.1117)	0.2673*** (0.0071)	0.2056** (0.0128)	0.0356 (0.3839)	-0.0320 (0.2225)
LJSEX (index)	0.3926*** (0.0015)	0.2562*** (0.0063)	0.2169*** (0.0051)	0.1199*** (0.0021)	0.0272 (0.2762)

Notes: In the parentheses under the GPH estimates of parameter *d*, the level of significance for rejecting the null hypothesis of stationary time series are denoted, calculated from OLS standard errors. Exceeded critical values for rejection of the null hypothesis are marked by *** (1% significance level), ** (5% significance level) and * (10% significance level).

Table 4. **The local Whittle estimator results of the parameter *d***

Stocks	Local Whittle estimator of Robinson (1995)		
	m = [$N^{0.5}$]	m = [$N^{0.7}$]	m = [$N^{0.8}$]
Aerodrom Ljubljana	0.2773*** (0.0668)	0.0685** (0.0297)	0.0160 (0.0198)
Gorenje	0.2243*** (0.0674)	0.0822*** (0.0303)	0.0675*** (0.0203)
Intereuropa	0.2445*** (0.0674)	0.0780*** (0.0299)	0.0386** (0.02)
Krka	0.0574 (0.0662)	0.04062 (0.0293105)	-0.0294 (0.0195)
Lasko	0.0872 (0.0700)	0.0282 (0.03188)	-0.0279 (0.0215)
Luka Koper	0.2201*** (0.0657)	0.0656** (0.0290)	0.0297 (0.0193)
Mercator	0.0682 (0.0651)	0.0075 (0.0286)	-0.0692*** (0.0190)
Petrol	0.1605** (0.0662)	0.0692** (0.0294)	0.0190 (0.0196)
Sava	0.2322*** (0.0700)	0.0453 (0.0318)	-0.0001 (0.0215)
LJSEX (index)	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).

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 Table 4 convey that as the bandwidth is increased, the estimates for the parameter *d* are lowered.

The local Whittle estimator results show that 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 at LJSEX also exhibit long memory, at least at some periodogram bandwidths.

The results of our study are in contrast to the findings of Jagric et al. (2005) who identified long memory in the returns of Slovenian stock markets. 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 Slovenian stock market, implies that stock returns follow a predictable behavior, which is inconsistent with the weak-efficiency market hypothesis. This may be due to the fact that Slovenian stock market has not attracted more serious foreign investors.

Conclusion. This study aimed to answer whether the returns at Slovenian stock market and individual stocks traded at Slovenian stock market 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 GPH (1984) estimator and the local Whittle estimator of Robinson (1995) we found that: i) Slovenian aggregated stock market returns (i.e., returns of the stock index) exhibit long memory; ii) the majority of Slovenian stock market returns were found to be characterized with a long memory property; iii) different methods of the fractional differencing parameter *d* yield similar conclusion regarding long memory evidence; iv) the results of long memory tests reject the weak form efficiency hypothesis for Slovenian stock market.

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