Silvo Dajcman[1]

A GEWEKE-PORTMAN-HUDAK TEST OF LONG-RANGE DEPENDENCE: A CASE OF INDIVIDUAL STOCKS AT THE STOCK MARKETS OF SLOVENIA, HUNGARY AND THE CZECH REPUBLIC

This paper answers whether the time series of returns of the stocks most traded at the stock markets of Slovenia, Hungary and the Czech Republic exhibit long-range dependence by applying the Geweke and Porter-Hudak (1983) method. The results suggest that long-range dependence is quite a common feature at the Slovenian stock market. Evidence of long-range dependence at the Czech stock market is weak while there is no evidence of long-range dependence in the returns of most commonly traded stocks listed at the Hungarian stock market.

Keywords: *long-range dependence; stock market; Geweke and Portman-Hudak method.*

JEL classification: G15; G11; F36.

Сільво Дайчман

ТЕСТ ДОВГОСТРОКОВОЇ ЗАЛЕЖНОСТІ ГЕВЕКЕ-ПОРТМАНА-ГУДАКА: НА ПРИКЛАДІ ОКРЕМИХ АКЦІЙ НА ФОНДОВИХ РИНКАХ СЛОВЕНІЇ, УГОРЩИНИ І ЧЕСЬКОЇ РЕСПУБЛІКИ

У статті перевірено довгострокову залежність часових рядів прибутковості акцій на фондових ринках Словенії, Угорщини і Чеської Республіки за допомогою тесту Гевеке і Портмана-Гудака (1983 рік). Результати показують, що довгострокова залежність — цілком звичайне явище на словенському фондовому ринку. Довгострокова залежність на чеському фондовому ринку слабка, тоді як немає жодних доказів довгострокової залежності прибутковості акцій на угорському фондовому ринку.

Ключові слова: *довгострокова залежність; фондовий ринок; метод Гевеке і Портмана-Гудака.*

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Сильво Дайчман

ТЕСТ ДОЛГОСРОЧНОЙ ЗАВИСИМОСТИ ГЕВЕКЕ-ПОРТМАНА-ГУДАКА: НА ПРИМЕРЕ ОТДЕЛЬНЫХ АКЦИЙ НА ФОНДОВЫХ РЫНКАХ СЛОВЕНИИ, ВЕНГРИИ И ЧЕШСКОЙ РЕСПУБЛИКИ

В статье проверена долгосрочная зависимость временных рядов доходности акций на фондовых рынках Словении, Венгрии и Чешской Республики путем применения теста Гевеке и Портмана-Гудака (1983 год). Результаты показывают, что долгосрочная зависимость — вполне обычное явление на словенском фондовом рынке. Долгосрочная зависимость на чешском фондовом рынке слабая, в то время как нет никаких доказательств долгосрочной зависимости доходности наиболее востребованных акций на венгерском фондовом рынке.

Ключевые слова: *долгосрочная зависимость; фондовый рынок; метод Гевеке и Портмана-Гудака.*

1. Introduction. A term "long-range dependence" (or "long memory") is used to describe the correlation structure of a series for long lags (Mandelbrot, 1977). The

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correlation of a time series with a long-range dependence decays slowly by a hyperbolic rate, meaning there is persistent temporal dependence even between distant observations. There are important implications for investors at stock markets when there is a long-range dependence in stock returns: optimal consumption/savings and portfolio decisions become extremely sensitive to investment horizon (Lo and MacKinlay, 2001), CAPM and APT are invalid (LeRoy, 1989), and the presence of long range dependence is an evidence against weak-form efficiency of a stock market (Barkoulas and Baum, 1996).

The long-range dependence property of a time series can be analyzed by a fractional integration parameter, d, that arises from the generalization of Box-Jenkins ARFIMA (autoregressive fractionally integrated moving average) model. The most prevalent method for estimating the fractional integration parameter d is Geweke and Porter-Hudak (GPH) (1983) method based on low-frequency spectral behavior of a time series.

The majority of the empirical studies on long-range dependence in stock markets returns are performed for developed stock markets (e.g., Ding et al., 1993; Lobato and Savin, 1998; Henry, 2002; Tolvi, 2003; Dajcman, 2011) and for markets as a whole (i.e., for stock indices). The earlier studies mostly found long-range dependence (e.g., Ding et al., 1993; Lobato and Savin, 1998), while the later provided only mixed evidence of the long-range dependence in stock market returns (e.g., Henry, 2002; Dajcman, 2011). There are only a few studies (e.g., Barkoulas and Baum, 1996) that investigate the long-range dependence of individual stocks in a particular stock market. Barkoulas and Baum (1996) noted that if long-range dependence 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 stock indices returns.

This paper answers whether the time series of the stocks most traded at the stock markets of Slovenia, the Czech Republic and Hungary exhibit long-range dependence by applying Geweke and Porter-Hudak (1983) method. In order to investigate whether the long-range dependence of individual stocks is indeed masked in the aggregate returns series, the fractional integration parameter d is estimated also for the main stock index of the respective countries.

2. Methodology

2.1. The long-range dependence property of time series. The long-range property of a time series can be analyzed by a fractional integration parameter, d, that arises from the generalization of Box-Jenkins ARFIMA (p, d, q) models from integer to non-integer values of the integration parameter d (autoregressive fractionally integrated moving average – ARFIMA models). A general class of fractional processes ARFIMA (p, d, q) is described as (Sadique and Silvapulle, 2001):

$$\Phi(B)(1-B)_t = \Theta(B)\varepsilon_t, \tag{1}$$

where X_t is a time series, $\Phi(B) = 1 - \varphi_1 B - \ldots - \varphi_p B^p$ and $\Theta(B) = 1 + \theta_1 B + \ldots + \theta_q B^q$ 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 $\varepsilon_t \sim IID(0, \sigma^2)$.

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. Hosking (1981) shows 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 $(I(0))$. The process with parameter d in range $0 < d < 0.5$ is said to exhibit long-range dependence. A process with parameter $-0.5 < d < 0$ also exhibits long-range dependence[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. When d is positive the sum of autocorrelations diverges to infinity, and collapses to zero when d is negative. A process with parameter $d \geq 0.5$ is not stationary and a shock in ε_t on X_t decays even more slowly. Characteristics of the fractionally integrated processes are summarized in Table 1.

Table 1. **Characteristics of the fractally integrated processes**

Value of the fractually integrated parameter d	Variance	Endurance of a shock, range of dependence	Stationarity of the process
-0.5 < d < 0	Finite	Long-run (long memory or long-run dependence)	Stationary
d = 0	Finite	Short-run (short-run deviation from mean value or a trend)	Stationary
0 < d < 0.5	Finite	Long-run (long-run deviation from mean value or trend, long memory or long-run dependence)	Stationary
0.5 < d < 1	Infinite	Long-run (long-run deviation from the mean value or trend, non-stationary long memory or long-run dependence)	Non-stationary
d = 1	Infinite	The process is non-mean reverting; deviation from the mean or a trend is permanent	Non-stationary
d > 1	Infinite	The process is non-mean reverting; deviation from the mean or a trend is permanent and explosive	Non-stationary

Source: Tkacz (2000).

2.2. The Geweke-Porter-Hudak (GPH) method. Geweke and Portman-Hudak (1983) devised an estimator 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 ordinary least squares 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:

[2] Processes with the parameter -0.5 < d < 0 are also called antipersistent, a terminology applied by Mandelbrot in numerous works.

$$\ln P_x(\lambda_s) = c - d\ln(4(\sin^2(\frac{\lambda_s}{2}))) + \varepsilon(\lambda_s), \quad (2)$$

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

$$\omega_x(\lambda_s) = (2\pi N)^{-\frac{1}{2}} \sum_{t=1}^{N} X_t e^{it\lambda_s}. \quad (3)$$

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 small will produce imprecise estimates of d. Geweke and Portman-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 $m = [N^{0.45}], [N^{0.55}]$ (Weron, 2002)).

Geweke and Portman-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 is performed on the basis of t-statistic 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. Charfeddine and Guegan (2007) prove that the method is robust only for $|d| < 0.5$.

3. Empirical results

3.1. Data. The long-range dependence is estimated for the most traded stocks listed in the main stock index of the respective countries (LJSEX for Slovenia, BUX for Hungary and PX for the Czech Republic). Stock (stock index) returns are calculated as the differences of logarithmic daily closing prices of stocks (i.e., $ln(P_t) - ln(P_{t-1})$, where P is a closing price). We endeavored to take the longest possible time of observation. The dates of observation for different stocks differ as not all stocks became listed at the stock market at the same time. The end date of observation is July 20, 2010. The stock prices were adjusted for stock splits or reverse stock splits.

Tables 2 to 4 present some descriptive statistics of the data. The data appear to be extremely non-normal. The majority of the return distributions are negatively skewed (especially at Hungarian and Czech stock markets), possibly due to the large negative returns associated with the financial crises in the observed period (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)). The data also appear leptocurtic. Jarque-Bera test rejects the hypothesis of normally distributed returns for all the stocks as well as stock indices.

Table 2. **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.	Skew-ness	Kur-tosis	Jarque-Bera statistics
Aerodrom Ljubljana	8.10.1997 - 20.7.2010	-0.1557	0.1656	0.0001783	0.01959	-0.05	9.81	6,167.71***
Gorenje	2.6.1998 - 20.7.2010	-0.0955	0.1045	0.0001288	0.01608	0.12	7.45	2,504.87***
Inte-reuropa	12.1.1998- 20.7.2010	-0.1016	0.1542	-0.000349	0.01634	0.31	12.15	10,955.89***
Krka	10.2.1997 - 20.7.2010	-0.2679	0.1984	0.000445	0.0179	-0.38	38.39	17,3381,37***
Lasko	1.2.2000 - 20.7.2010	-0.1504	0.1263	-0.0001871	0.01995	-0.16	9.41	4,476.48***
Luka Koper	20.11.1996 - 20.7.2010	-0.0965	0.1281	0.00006687	0.01724	-0.03	7.95	3,474.08***
Mercator	4.4.1996 - 20.7.2010	-0.1751	0.1554	0.0005507	0.01883	0.23	13.94	17,803,66***
Petrol	5.5.1997 - 20.7.2010	-0.102	0.1328	0.0002867	0.01623	0.33	11.09	9,062.37***
Sava	6.1.2000 - 20.7.2010	-0.1274	0.1535	0.0002616	0.0181	0.01	9.84	5,120.06***
LJSEX (stock index)	4.4.1996 - 20.7.2010	-0.1161	0.1893	0.0002782	0.01183	0.35	34.16	144,220.93***

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

Table 3. **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.	Skew-ness	Kurtosis	Jarque-Bera statistics
ANY	8.12.2005 - 12.5.2010	-0.1316	0.1214	0.0002407	0.02034	-0.43	10.37	2,534.35***
Egis	1.4.1997 - 12.5.2010	-0.3567	0.1944	0.0002173	0.02676	-0.97	20.41	41,904.65***
Fotex	1.4.1997 - 12.5.2010	-0.3365	0.2346	0.0002929	0.03281	0.40	13.60	15,419.85***
MOL	1.4.1997 - 12.5.2010	-0.2231	0.1403	0.0005836	0.02449	-0.21	9.70	6,153.19***
MTelekom	14.11.1997 - 12.5.2010	-0.1257	0.1199	-0.0000307	0.02136	-0.20	6.67	1,769.98***
OTP	1.4.1997 - 12.5.2010	-0.2513	0.2092	0.0008684	0.02782	-0.22	10.80	8,321.11***
Pannergy	1.4.1997 - 12.5.2010	-0.2076	0.2343	-0.0001887	0.02674	0.20	11.68	10,304.38***
Raba	17.12.1997 - 12.5.2010	-0.2501	0.1999	-0.000373	0.026	-0.14	12.56	11,794.59***
Richte	1.4.1997 - 12.5.2010	-0.231	0.2178	0.000404	0.0262	-0.63	16.39	24,698.68***
Synergon	5.5.1999 - 12.5.2010	-0.1625	0.1526	-0.000558	0.02986	0.41	8.63	3,724.70***
TVK	1.4.1997 - 12.5.2010	-0.2231	0.2068	0.0001	0.02755	-0.15	11.84	10,683.4***
BUX (stock index)	1.4.1997 - 12.5.2010	-0.1803	0.1362	0.0004538	0.01924	-0.64	13.18	14,367.97***

Note: See notes for Table 2.

Table 4. **Descriptive statistics for returns series of stocks listed at Prague stock exchange and the representative stock index**

Stock/ stock index	Period of obser.	Min	Max	Mean	Std. d.	Skew-ness	Kurtosis	Jarque-Bera statistics
Auto Group	26.9.2007 - 12.5.2010	-0.1777	0.383	-0.001818	0.037743	1.69	25.23	13,760.99***
CETV	26.9.2007 - 12.5.2010	-0.237	0.3075	-0.001797	0.04803	0.28	9.01	991.58***
CEZ	10.1.1995 - 12.5.2010	-0.1539	0.204	0.0006165	0.02407	-0.32	8.52	4,626.25***
ECM Real Estate	1.11.1997 - 12.5.2010	-0.2707	0.3381	-0.002823	0.04049	0.64	17.94	5,895.57***
Erste Group Bank	26.9.2007 - 12.5.2010	-0.1836	0.1632	-0.0008791	0.03751	-0.11	7.37	521,34***
Komercni Banka	10.1.1995 - 12.5.2010	-0.2076	0.1594	0.0002444	0.02684	-0.32	7.62	3,263.82***
ORCO	26.9.2007 - 12.5.2010	-0.3185	0.2646	-0.004266	0.05067	-0.07	9.55	1,169.40***
Philip Moris	10.1.1995 - 12.5.2010	-0.1634	0.1263	0.0002033	0.02435	-0.31	6.94	2,386.91***
Telefonica	28.3.1995 - 12.5.2010	-0.1281	0.1299	0.0001179	0.02184	-0.02	6.93	2,316.04***
Unipetrol	26.8.1997 - 12.5.2010	-0.1704	0.1799	0.0001473	0.0263	-0.13	7.61	2,829.18***
PX (index)	09.1.1996 - 12.5.2010	-0.1619	0.1236	0.0002807	0.01492	-0.41	14.88	21,256,18***

Note: See notes for Table 2.

3.2. Results of GPH method. The null hypothesis in GPH method, i.e. that the time series is stationary $(H_0 : d = 0)$, was tested against the alternative hypothesis of long-range dependence in a time series $(H_0 : d = 0)$. In order to check the robustness of 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 $m = [N^{0.8}]$. The results are summarized in Tables 5 through 7.

Table 5. **The GPH estimator of parameter d for Slovenian stock market**

	$m = [N^{0.45}]$	$m = [N^{0.5}]$	$m = [N^{0.55}]$	$m = [N^{0.7}]$	$m = [N^{0.8}]$
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)

The End of *Table 5*

	m = [$N^{0.45}$]	m = [$N^{0.5}$]	m = [$N^{0.55}$]	m = [$N^{0.7}$]	m = [$N^{0.8}$]
LJSEX (stock 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 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 6. **The GPH estimator of parameter d for Hungarian stock market**

	m = [$N^{0.45}$]	m = [$N^{0.5}$]	m = [$N^{0.55}$]	m = [$N^{0.7}$]	m = [$N^{0.8}$]
ANY	0.0384 (0.7993)	0.0943 (0.4423)	0.1740* (0.0741)	0.0773 (0.2159)	-0.0726* (0.1074)
Egis	0.0341 (0.7975)	0.1283 (0.2085)	0.0862 (0.2624)	0.0317 (0.3988)	0.0127 (0.6199)
Fotex	0.1416 (0.3082)	0.0801 (0.4212)	-0.0301 (0.6937)	0.0488 (0.2191)	0.0480* (0.0695)
MOL	0.0587 (0.5828)	0.0052 (0.9542)	0.0233 (0.7289)	-0.0245 (0.4922)	-0.0134 (0.5854)
MTelekom	-0.0282 (0.7821)	-0.0774 (0.3411)	0.0102 (0.8879)	-0.0180 (0.6455)	-0.0117 (0.6496)
OTP	-0.0470 (0.5994)	0.0753 (0.3989)	0.1320* (0.0775)	0.0317 (0.4265)	0.0033 (0.9020)
Pannergy	0.1406 (0.3000)	0.0430 (0.6592)	0.0738 (0.3516)	0.0212 (0.5942)	0.0114 (0.6677)
Raba	0.1938 (0.1190)	0.0606 (0.5441)	0.0694 (0.3907)	-0.0274 (0.4960)	0.0167 (0.5336)
Richte	-0.0577 (0.6609)	-0.1216 (0.1833)	-0.0414 (0.5387)	-0.0369 (0.3279)	-0.0105 (0.6933)
Synergon	0.1155 (0.4041)	0.0950 (0.4131)	0.0306 (0.7092)	0.0491 (0.2350)	0.0860*** (0.0032)
TVK	-0.0732 (0.5529)	-0.0785 (0.3820)	0.0181 (0.8126)	-0.0257 (0.4768)	0.0221 (0.3968)
BUX (stock index)	0.0067 (0.9570)	-0.0357 (0.6857)	0.0447 (0.5039)	0.0510 (0.2175)	0.0345 (0.2065)

Notes: See notes for Table 5.

Table 7. **The GPH estimator of parameter d for Czech stock market**

	m = [$N^{0.45}$]	m = [$N^{0.5}$]	m = [$N^{0.55}$]	m = [$N^{0.7}$]	m = [$N^{0.8}$]
Auto Group	0.1007 (0.5663)	0.0996 (0.4435)	0,1394 (0.1842)	0.1322* (0.0764)	0.1143** (0.0313)
ECM Real Estate	0.1750 (0.3410	0.1724 (0.2181	0.1498 (0.2372)	0.0028 (0.9706)	0.0043 (0.9323)
Erste Group Bank	0.2378 (0.2638)	0.1594 (0.2851)	0.1496 (0.2305)	0.0452 (0.4691)	0.0374 (0.4000)
CETV	0.2108 (0.2538	0.1973 (0.1922	0.2671** (0.0339)	0.1397* (0.0463)	0.1020* (0.0280)
CEZ	0.0559 (0.6553)	0.0565 (0.5360)	0.0756 (0.2838)	0.0164 (0.6711)	-0.0229 (0.3783)
Komercni Banka	0.0890 (0.3149)	0,0939 (0.2479)	0.0550 (0.4150)	0.0595 (0.1130)	0.0267 (0.2759)
ORCO	0.0601 (0.7938)	0.0059 (0.9704)	0.0572 (0.6585)	-0.0850 (0.2992)	-0.0392 (0.4351)

The End of *Table 7*

	$m = [N^{0.45}]$	$m = [N^{0.5}]$	$m = [N^{0.55}]$	$m = [N^{0.7}]$	$m = [N^{0.8}]$
Philip Moris	-0.0022 (0.9843)	-0.0255 (0.7648)	-0.0569 (0.3757)	0.0085 (0.8109)	-0.0163 (0.4931)
Telefonica	-0.0846 (0.5389	-0.0040 (0.9718)	-0.0425 (0.6016)	-0.0127 (0.7607)	-0.0437* (0.0808)
Unipetrol	0.1157 (0.4779)	0.0420 (0.7213)	0.1024 (0.2497)	-0.0513 (0.2014)	-0.0543** (0.0360)
PX (stock index)	0.0832 (0.3802)	0.0880 (0.2871)	0.1954*** (0.0139)	0.0813* (0.0574)	0.0078 (0.7619)

Notes: See notes for Table 5.

As Table 5 demonstrates, there is evidence that Slovenian stock market exhibits fractional dynamics with long-range dependence features. However, the results are sensitive to the number of frequencies included in the calculation of GPH estimator. When only lower frequencies $m = [N^{0.45}] \leq m \leq [N^{0.55}]$ are included in the GPH estimator, the null of an $I(0)$ process can be rejected for stock of Aerodrom Ljubljana, Gorenje, Intereuropa, Lasko, Luka Koper, Petrol, Sava and for the stock market index (LJSEX index). At all the frequencies of the periodogram, Gorenje, Intereuropa and the LJSEX index exhibited long-range dependence in returns. The results suggest that long-range dependence in stock returns is quite a common feature for Slovenian stock market.

The results of GPH method for Hungarian stock market (Table 6) show that the returns of shares listed at BUX and BUX itself are stationary. The results hold true for all the numbers of frequencies included in the calculation of GPH estimator. Thus there is no evidence of long-range dependence at Hungarian stock market.

For Czech stock market, the findings of GPH (Table 7) are similar to the findings of Hungarian stock market, yet they show a weak long-range dependence for some of the listed stocks. There is only a weak evidence (found only for one of the included frequencies in the calculation of GPH estimator) against the stationarity of the return time series for Unipetrol, CETV, Auto Group and the PX index.

The long-range dependence found in the returns of Slovenian stocks and stock market index implies that stock returns follow a predictable behavior, which is inconsistent with the weak-form efficiency market hypothesis. The results of long-range dependence estimator for Hungarian stock market do not reject the weak-form efficiency hypothesis. The evidence against the weak-form efficiency hypothesis validity for Czech stock market is weak.

Conclusion. This paper answers whether the time series of the stocks most traded at the stock markets of Slovenia, the Czech Republic and Hungary exhibit long-range dependence by applying Geweke and Porter-Hudak (1983) method. In order to investigate whether the long-range dependence of individual stocks is indeed masked in the aggregate returns series, the fractional integration parameter   is estimated also for the stock main stock index of the respective countries.

The results suggest that long-range dependence is quite a common feature for Slovenian stock market. There is no evidence of long-range dependence for any of the stocks listed at Hungarian stock market nor its main stock market index. Evidence against stationarity of return time series in the Czech market is weak (i.e., found only for one of the included frequencies at calculation of GPH estimator).

The long-range dependence found in the returns of Slovenian stocks and stock market index implies that stock returns follow a predictable behavior, which is inconsistent with the weak-form efficiency market hypothesis. The results of long-range dependence estimator for Hungarian stock market do not reject the weak-form efficiency hypothesis. The evidence against the weak-form efficiency hypothesis validity for Czech stock market is weak.

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