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Financial crisis influence on the BUX index of Hungarian Stock Exchange. Long memory measures: 1991-2008

Ewa M. Syczewska
Warsaw School of Economics

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Ewa Marta Syczewska
Warsaw School of Economics[1]

Abstract

We analyze daily quotes of the BUX index, main index of the Budapest stock exchange, for period 2nd Jan. 1991–30th Sept. 2008, checking nonstationarity of series, stationarity of returns, applying the ARCH tests to the series. This period was not without its perils for the Hungarian economy. We check presence of long memory of the series with use of classification based on the Hurst index and fractional integration parameter estimates. We analyze sample ACF and PACF functions and fractional integration estimates also for squared returns of the index. Volatility of returns and squared returns increases towards the end of sample, in agreement with the fact of risk growth due to the global crisis. In last part of sample the series of returns was antipersistent, changing sign more often, and the series was more volatile. Graphs of spectrum for the series show different behavior of logarithmic returns (more volatile towards the end of sample) and similar for squared returns throughout the sample.

JEL classification: C220, G19

Keywords: unit root, nonstationarity, spectral analysis, long memory, random walk, fractional integration, stock exchange index, volatility, risk

[1] Contact: Warsaw School of Economics, Institute of Econometrics, Al. Niepodległości 162, 02–554 Warsaw, Poland. E-mail: Ewa.Syczewska@sgh.waw.pl

1. Introduction

Inspiration for this research came from study of difficulties caused for the Hungarian economy by financial crisis and economic and political instability[2]. Problems of Hungary were already signalized by such institutions as European Central Bank, IMF (in its country reports), Magyar Nemzeti Bank (the Hungarian central bank). Hard times for Hungary were painful also for other countries of the region, who – in spite of their relatively better standing – were treated by some foreign investors in the same way as one group of emerging markets.

In this study we analyze series of daily quotes of main Hungarian stock exchange index, BUX, and its logarithmic returns, seeking for any symptoms of structural changes. We use both tools of time series analysis, nonstationarity and stationarity tests, and methods of classification of time series behavior based on fractional integration parameter estimates and on Hurst exponent. We want to know whether there was any possibility to foretell incoming crisis on base of such indicators. Long memory of a series and divergence form the random walk process can be used also as indicator of market efficiency, and long-term dependence between squared values and their lags (an ARCH effect) means that there is a possibility of ARCH and GARCH modeling.

The data come from the Magyar Nemzeti Bank data base and are daily quotes of the BUX index, since 2nd January 1991 until 30th September 2008. Computations were performed mainly with use of *Gretl* econometric package (see *gretl.sourceforge.net*, or www.kufel.torun.pl for the Polish version).

2. Crisis influences the Hungarian economy

Disturbances on the financial markets caused by the subprime crisis in the US influenced global markets, and Hungarian economy among others. Risk premia for instruments denominated in forints have increased and their liquidity decreased. Due to worsening of the economy perspectives, high foreign debt, and liquidity constraints, the Hungarian instruments are less ansd less attractive for foreign investors. Both liquidity constraints and tighter bank credit requirements can negatively influence Hungarian firms in long term. Decrease of internal demand, investments and worsening conditions of labor market diminish growth rate (see. Magyar Nemzeti Bank, *Report on Financial Stability, April 2008*).

[2] First version of this text was prepared as part of statutory research „Makro- i mikroekonometria: zastosowania ekonomiczne i finansowe" (Macro- and microeconometrics: applications in economics and finance) No 03 / S / 0053/ 08, Institute of Econometrics, Warsaw School of Economics.

Table 1 prepared by the MNB based on Bloomberg data shows rating of foreign debt of countries of the region in Spring 2008, by Moody's, Standard&Poor's and Fitch. Symbols denote respectively:

– - negative rating   M – Moody's

~ - stable rating   F – Fitch

+ - positive rating   SP – Standard &Poor's

TABLE 1. Rating of foreign debt, countries of Central and Eastern Europe

Moody's	Estonia			Latvia			Lithuania			Bulgaria			Romania			Czech Republic			Poland			Slovakia			Hungary			S&P;Fitch
	M	SP	F	M	SP	F	M	SP	F	M	SP	F	M	SP	F	M	SP	F	M	SP	F	M	SP	F	M	SP	F	
Aaa																												AAA
Aa1																												AA+
Aa2																												AA
Aa3																+												AA–
A1	~																~	~										A+
A2		–	–	~			~		–										~			~						A
A3								–												~	~		+	~				A–
Baa1					–	–				~																–	~	BBB+
Baa2											–				–													BBB
Baa3										+			~	–														BBB–

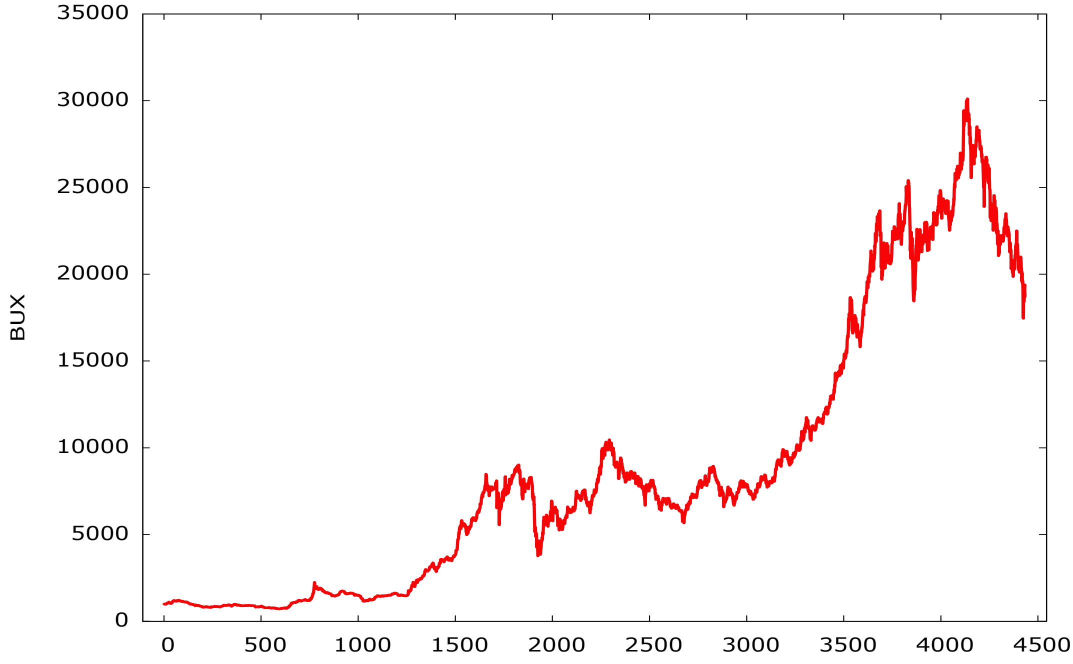
Source: table 1-1, „Ratings on long-term sovereign debt of regional countries", in: Magyar Nemzeti Bank "Report on Financial Stability, April 2008".

All those factors led to deterioration of foreign investors attitude towards Hungarian economy (and other so-called emerging markets). One of main factors was huge slide on the Hungarian Stock Exchange. Graph of the main Hungarian index, for period since 3rd January 1991 until 30th September 2008, shows increasing trend for most of the period, and then deterioration near the end of the sample.

The graph of logarithmic returns for the BUX index, $r_t = \ln p_t - \ln p_{t-1}$, suggests high volatility for observations number 1700-2000, i.e., in period since September 1997 until the end of 1998. Since then volatility is much higher than in previous years. Another period of huge volatility increase is in Autumn 2008.

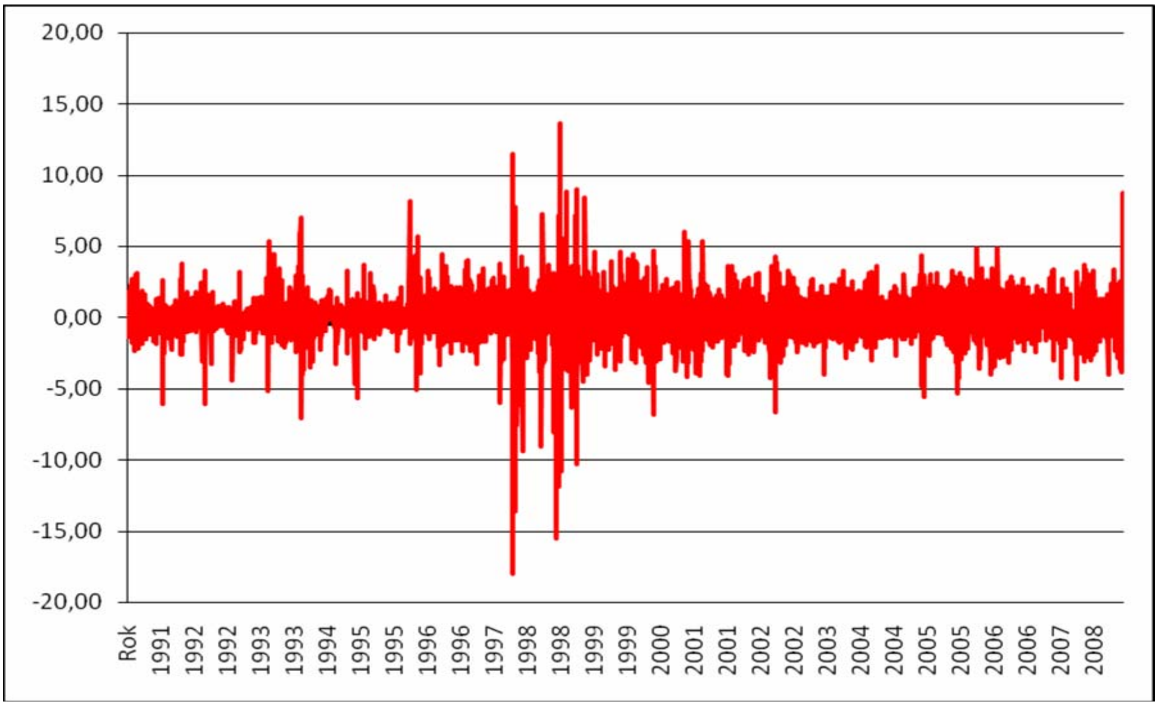
We check whether quotes of the BUX index and returns have features typical for financial instruments, and how decrease of this index in 2008 influences results of tests.

FIGURE 1. Daily quotes of the BUX index, 01.1991 09.2008



Source: own computations based on the MNB data

FIGURE 2. Logarithmic returns of the BUX index for the same period



Source: own computations based on the MNB data

3. Autocorrelation and partial autocorrelation function for the BUX index

One of tools of checking long-memory in time series, and – in Box-Jenkins methodology – also of choice of ARMA/ARIMA model specification, is sample autocorrelation and partial autocorrelation function. Also test of joint significance of autocorrelation coefficients can be used. The Ljung-Box test statistics for joint significance of autocorrelation coefficients up to k lags has χ^2 distribution with k degrees of freedom. If a computed value is larger than a critical value, null of no significance has to be rejected (as it is in our example)[3].

Visual analysis of autocorrelation function is also important – in case of stationary series autocorrelation will diminish with increase of lags number. If ACF diminishes only slowly, this can suggest that a series in question is nonstationary and has long memory.

The sample ACF and PACF for the BUX index suggest that it is nonstationary, and that AR(1) model error terms can be used for the ARCH effect test. The ACF coefficients are significant at least up to lag k = 14, and the graph shows no tendency for them to diminish in time.

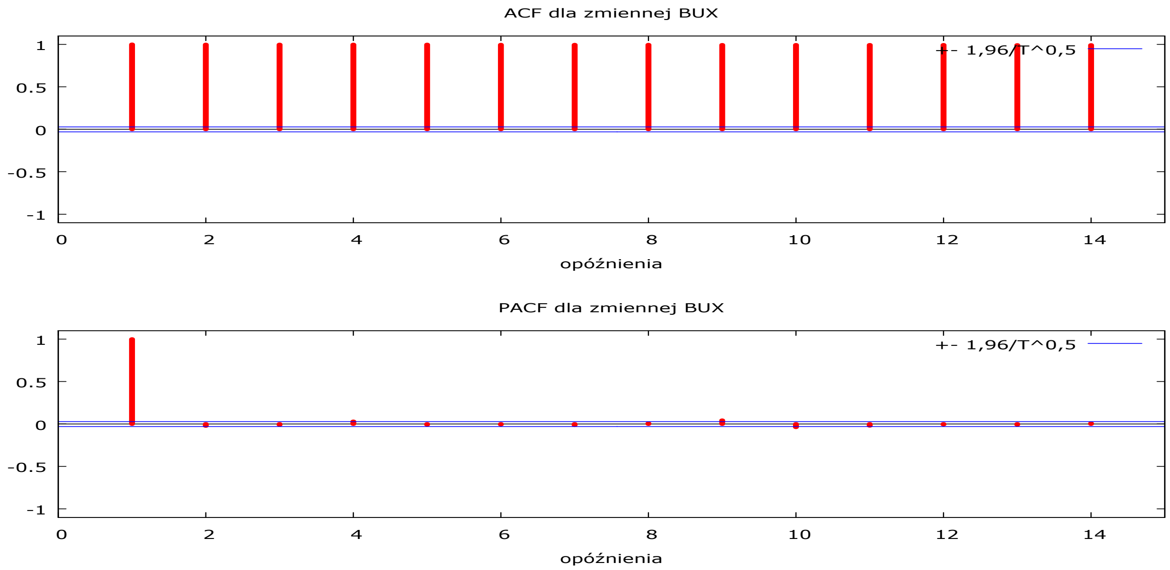
TABLE 2. Autocorrelation function (ACF) and partial autocorrelation function (PACF), the Ljung=Box autocorrelation test (Q) for the BUX daily quotes

Lags	ACF	PACF	Ljung-Box Q	[p-value]
1	0.9995 ***	0.9995 ***	4431.1749	[0.000]
2	0.9989 ***	-0.0218	8858.3177	[0.000]
3	0.9983 ***	-0.0086	13281.3451	[0.000]
4	0.9978 ***	0.0304 **	17700.5502	[0.000]
5	0.9972 ***	-0.0063	22115.8878	[0.000]
6	0.9967 ***	-0.0060	26527.3071	[0.000]
7	0.9961 ***	-0.0124	30934.6804	[0.000]
8	0.9955 ***	0.0080	35338.0853	[0.000]
9	0.9950 ***	0.0441 ***	39737.9533	[0.000]
10	0.9945 ***	-0.0382 **	44133.9482	[0.000]
11	0.9939 ***	-0.0199	48525.8695	[0.000]
12	0.9933 ***	-0.0059	52913.6229	[0.000]
13	0.9927 ***	-0.0067	57297.1653	[0.000]
14	0.9921 ***	0.0081	61676.5881	[0.000]

[3] Three stars denote significance at 1%, two stars – at 5%.

Source: own computations

FIGURE 3. Autocorrelation and partial autocorrelation function for the BUX index, 3rd January 1991-30th September 2008.



Source: own computations

TABLE 3. Autocorrelation function (ACF) and partial autocorrelation function (PACF), the Ljung-Box test (Q) for BUX index returns.

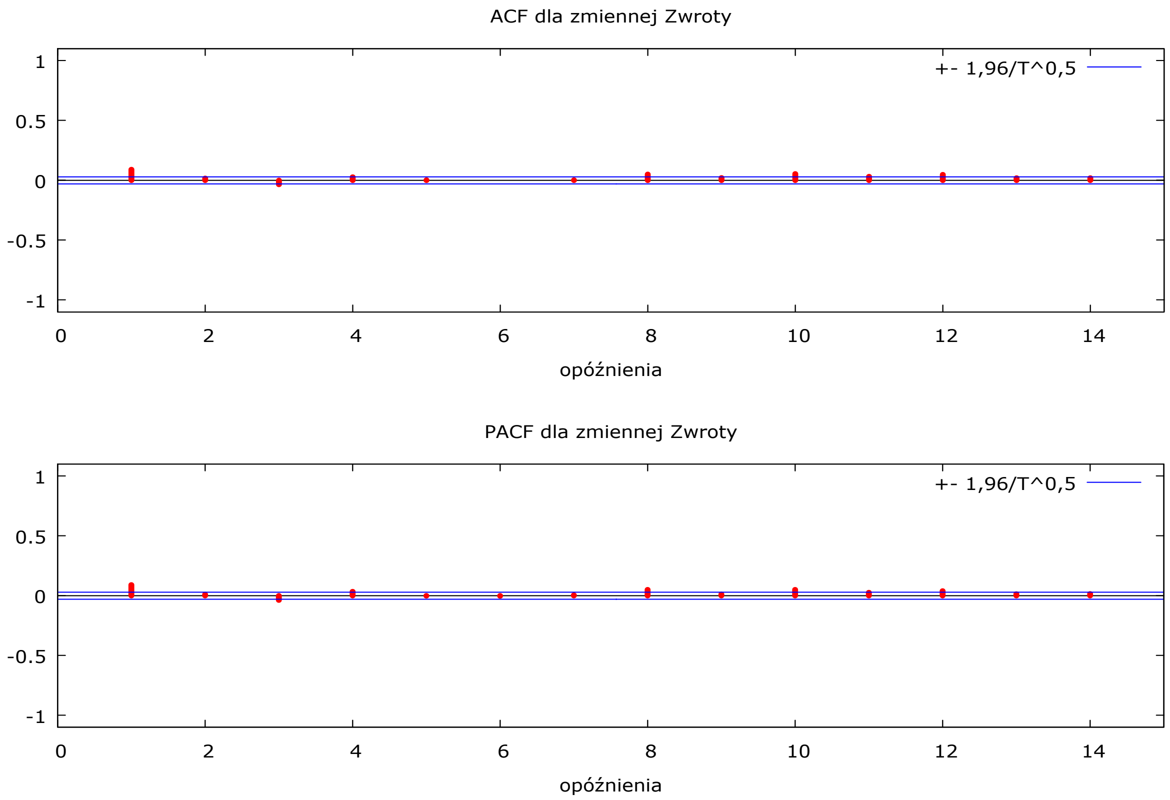
Lags	ACF	PACF	Ljung-Box Q	[p-value]
1	0.0904***	0.0904***	36.2801	[0.000]
2	0.0178	0.0097	37.6835	[0.000]
3	-0.0347**	-0.0375**	43.0276	[0.000]
4	0.0274*	0.0340**	46.3677	[0.000]
5	0.0023	-0.0022	46.3908	[0.000]
6	-0.0004	-0.0028	46.3913	[0.000]
7	0.0019	0.0046	46.4076	[0.000]
8	0.0507***	0.0498***	57.8211	[0.000]
9	0.0209	0.0117	59.7579	[0.000]
10	0.0545***	0.0509***	72.9537	[0.000]
11	0.0325**	0.0267*	77.6458	[0.000]
12	0.0479***	0.0400***	87.8564	[0.000]
13	0.0203	0.0151	89.6817	[0.000]

Lags	ACF	PACF	Ljung-Box Q	[p-value]
14	0.0204	0.0159	91.5270	[0.000]

Source: own computations

FIGURE 4.

Sample autocorrelation function and partial autocorrelation function for returns of the BUX index.



Source: own computations

The same ACF and PACF functions for *returns* have completely different characteristics. There is no strong correlation between correlation coefficients with lagged values of returns. The autocorrelation function is decreasing with increase of lags k .

According to the Box-Jenkins methodology, based on analysis of ACF and PACF graphs, as model appropriate to description of the BUX index we can choose an ARIMA model. Nonstationarity test ADF and stationarity test KPSS show that first difference is enough for achieving stationarity.

4. ADF and KPSS tests for the BUX index

The random walk process, often used in financial analysis, assumes that a variable y_t is generated by an equation of autoregression AR(1):

$$y_t = y_{t-1} + \varepsilon_t$$

where error terms ε_t are i.i.d. If in addition the process is starting in 0, it can be easily shown that

$$y_t = \sum_{i=1}^{t} \varepsilon_i$$

Hence influence of a shock ε_t do not diminish with time, but tend to last forever (the process has long memory). This is a non-stationary process (eg., its variance increases with time), but its differences are stationary, which can be checked with use of unit-root tests (Dickey-Fuller or augmented Dickey-Fuller unit root test, ADF in short, see Dickey and Fuller [1979] and Said and Dickey [1985]) or stationarity tests (eg., Kwiatkowski, Phillips, Schmidt and Shin test, KPSS in short, see Kwiatkowski *et al*. [1992]).

The random walk process corresponds to idea of weak market efficiency, where price of instruments cannot be foreseen with use of information of past values only (see Czekaj *et al*. [2001], pp. 77–78).

The augmented Dickey-Fuller test regression is of the form:

$$\Delta y_t = \mu + \delta y_{t-1} + \sum_{j=1}^{k} \gamma_j \Delta y_{t-j} + \varepsilon_t$$

The test statistic is defined as DF = $\hat{\delta} / s_{\hat{\delta}}$, to be compared with a proper critical values. If a computed value is greater than a critical value, the null of nonstationarity cannot be rejected.

In the KPSS test, conversely, the null corresponds to stationarity of a series. Its values are generated by the process

$$y_t = r_t + \xi t + \varepsilon_t$$
$$r_t = r_{t-1} + u_t$$

If variance of u_t is equal to zero, $r_t = r_0 =$ constans, hence y_t is sum of a trend and stationary error term, which corresponds to a null of stationarity around a trend. If variance of u_t is positive, r_t is a random walk process, hence y_t is also nonstationary. The KPSS test with its reversed hypotheses can be treated as complementary to the ADF test.

The results of augmented Dickey-Fuller test for the BUX index are as follows. With 14 lags (which corresponds approximately to two weeks) in test regression with a constant, computed value of the test statistic equals –0.487 (p-value 0.89), in a regression with a constant and linear trend DF = –1.909 (p-value 0.65).

Both versions indicate that null of nonstationarity cannot be rejected. On the other hand, the KPSS test has stationarity as a null hypothesis. The KPSS test statistics equal to 4.147 is higher than the critical value, hence the null of stationarity is rejected. Both tests give the same result, i.e. the BUX index is nonstationary (in perfect agreement with our knowledge about stock indices behaviour).

Results of the tests for the BUX returns are as follows. The ADF test statistics with a constant without a trend is –17.17, less than a critical value, hence the null of nonstationarity is rejected. The KPSS test statistics without trend equals 0.113 (with critical value 0.347 for 10%, 0.463 for 5%). The KPSS null of stationarity cannot be rejected.

5. Measures of long memory: fractional integration parameter and the Hurst exponent for the BUX index

More detailed description of behaviour of the series is with use of fractional integration parameter or the Hurst exponent (introduced in Hurst [1951]). There are several methods of fractional integration parameter estimation, based on periodogram regression (the Geweke and Porter-Hudak [1983] method, the Philips [1999] method). There are also nonparametric methods of computing parameters describing series dynamics – rescaled range method and the more general Andrew Lo [1991] method. On the other hand, the Hurst exponent can be computed with use of regression of periodogram logarithm on logarithms of numbers of observations in subsamples.

5.1. The Hurst exponent

The Hurst exponent construction has had its source in Hurst studies on long-term data of the Nile river floods and level changes. He measured changes of water levels of Nile dam and compared them with the mean, amplitude of changes divided by standard deviation, and get the rescaled range R/S statistics. He noted that such processes can be described by the random walk with drift model. The influence of this drift, or trend, can be measured by changes of R/S as a function of time (Peters [1997] p. 64-65).

The Hurst exponent is equal to slope of regression line of natural logarithms R/S on logarithms of subsamples numbed of observations, t (in computations either all divisors of whole sample size, T, is used, or consecutive powers of 2 less or equal to T), hence

$$\ln(R/S)_i = \ln(t_i) + \ln a$$

If number of observations is small, H can be computed from a formula

$$H = \ln(R/S)/\ln([0.5T])$$

where: T – number of observations in whole sample,

t_i – divisors of T (or powers of 2 not greater than T).

According to the Hurst exponent values, a classification of series behavior can be formulated as follows. If H = 0.5, we have random walk process, consecutive realizations of a series are independent – there are no dependencies, even in very long time (Czekaj et al. [2001], p. 89).

For $0 \le H < 0.5$ the process is antipersistent, diverging from the mean. It is more volatile than the random walk process (after negative values it takes more often positive values than after positive ones) (see Peters [1997] p. 66-67). It is sometimes called a pink noise. Czekaj *et al*. [2001], p.89, note that the only antipersistent series among financial data is volatility (risk) of financial markets.

For 0.5 < H < 1 series is persistent, mean-reverting, it is sometimes called black noise (Czekaj *et al*. [2001] p. 89-90), and has tendency to maintain the trend, stronger for H closer to 1. With increase of H correlation of signs of observations is stronger, and the graph of the series gets more smooth (Peters [1997], p. 67 and 69).

Our data sample has 4433 observations, hence it has 10 integral divisors, corresponding to subsamples used for the H computations (see table 4). Results of OLS estimation of rescaled range logarithm on logarithm of number of observations in particular subsamples are the following (with estimation errors in parentheses):

$$\ln(R/S)_i = \underset{(0.104)}{-0.253157} + \underset{(0.013)}{0.59742}(\ln N)_i$$

The Hurst exponent estimate is equal to slope of this regression, hence it is greater than 0.5. According to the aforementioned classification, we have here persistent series. Note that this value of the Hurst exponent is quite close to Czekaj *et al*. [2001] estimates of the Hurst exponent for WIG and MIDWIG indices of the Warsaw stock exchange. Their estimates are close to 0.55, and our estimate for the BUX index is slightly greater, close to 0.60, which suggests stronger persistence (trend maintaining tendency) than for the Warsaw stock exchange of earlier period.

TABLE 4. The Hurst exponent computations

(1) Number of observations in a subsample	(2) RS(avg)	Logarithm of (1)	Logarithm of (2)
4433	109.62	12.114	6.7764
2216	79.95	11.114	6.321
1108	61.75	10.114	5.9484
554	38.677	9.1137	5.2734
277	25.555	8.1137	4.6756
138	17.107	7.1085	4.0965
69	10.594	6.1085	3.4051
34	6.8446	5.0875	2.775
17	4.4049	4.0875	2.1391
8	2.7107	3	1.4387

Source: own computations.

5.2. Periodogram and fractional integration parameter estimates

The Hurst exponent and the fractional integration parameter can be also used to classify a series according to characteristics such as stationarity, long or short memory, mean reversion or mean aversion, reaction to external shocks. Fractional integration parameter d greater than 0.5 characterizes nonstationary series, but if $d < 1$, the series is mean-reverting in the long run. Value of d greater than 1 shows that the series in question is nonstationary and influence of external shocks increase in time.

The fractional integration parameter estimates for the BUX index, until 2008, are as follows.

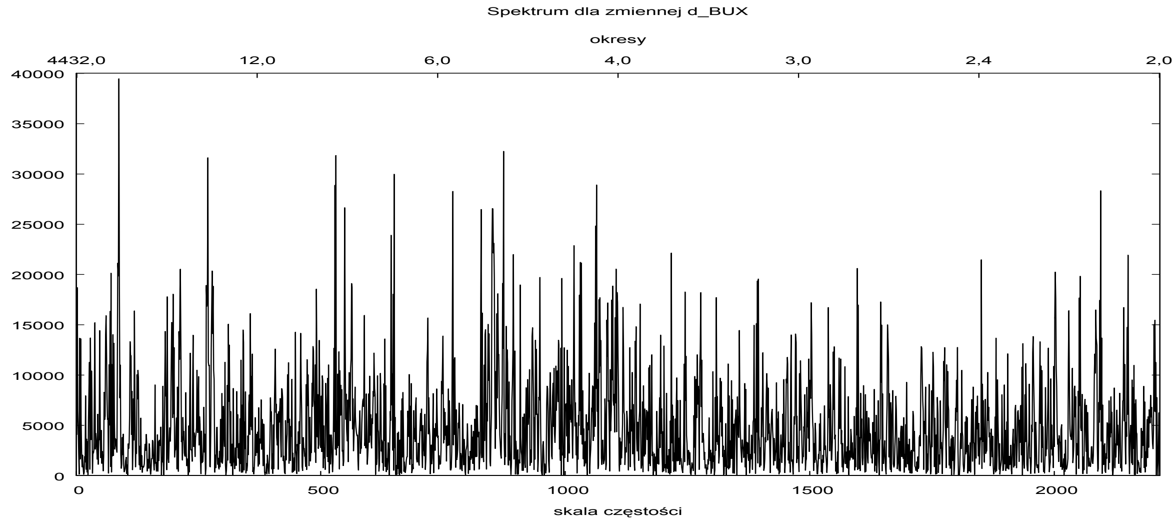
```
The GPH (Geweke and Porter-Hudak) test for fractional integration parameter (m = 256)
  Estimate of fractional integration parameter = 1.04892 (0.0288779)
  Test statistics: t(254) = 36.3225, p-value 0.0000

Local Whittle estimator (m = 256)
  Estimate of fractional integration parameter = 1.04086 (0.03125)
  Test statistics: z = 33.3077, p-value 0.0000
```

Periodogram of a nonstationary process, according to Granger [1966], for an argument close to zero, goes to infinity. This is so for the BUX index. After computing either differences or logarithmic returns for the index, periodogram behaves in a way typical for stationary variables (see Fig. 5).

Our estimates of fractional integration parameter obtained with the Geweke and Porter-Hudak method and Whittle method are equal respectively to1.04892 and 1.04086. Hence they are greater than zero, which perhaps means that the series is unstable and for sure marks its nonstationarity. The GPH method is known to work better for stationary than for nonstationary series. Hence we repeat computations for the logarithmic returns of the BUX index.

FIGURE 5. Spectrum of the returns of BUX indeks, whole sample



Source: own computations

The results of computations are following:

```
The GPH (Geweke and Porter-Hudak) estimator of fractional integration parameter (m = 153)
  Estimate of fractional integration parameter = 0.0301544 (0.0560317)
  Test statistics: t(151) = 0.538166, p-value 0.5913

The Whittle local estimator (m = 153)
  Estimate of fractional integration parameter = 0.0314908 (0.0404226)
  Test statistics: z = 0.77904, p-value 0.4360
```

We can see that now estimates of fractional integration parameter are low, positive and close to zero. This means stationarity of the BUX returns.

Fractional integration parameter D for a series and d for its differences in theory fulfill condition $D = d+1$, hence we can assume that fractional integration parameter for the BUX index should be close to 1 (maybe slightly larger than 1). This suggests instability of a series and lack of stationarity.

5.3. Fractional parameter estimates for subsamples

We have shown results of the fractional integration parameter estimation for the whole period 1991-2008, which by no means is homogeneous in terms of economic conditions. Now we divide the whole sample in four parts, with similar numbers of observations. To estimate fractional integration parameter we need quite high number of observations, hence we choose four subsamples with more or less a thousand observations.

Period 1: observations 1–1024

Periodogram for: d_BUX

Number of observations = 1024

The GPH (Geweke and Porter-Hudak) fractional integration parameter (m = 63)

Estimate of fractional integration parameter = **0.267898** (0.0843702)

Test statistics: t(61) = 3.17527, p-value 0.0023

The Whittle local estimator (m = 63)

Estimate of fractional integration parameter = **0.243746** (0.0629941)

Test statistics: z = 3.86935, p-value 0.0001

Period 2:observations 1025–2048

The GPH (Geweke and Porter-Hudak) fractional integration parameter (m = 62)

Estimate of fractional integration parameter = **0.317726** (0.0765489)

Test statistics: t(60) = 4.15063, p-value 0.0001

The Whittle local estimator (m = 62)

Estimate of fractional integration parameter = **0.320793** (0.0635001)

Test statistics: z = 5.05185, p-value 0.0000

Period 3: observations 2049–3072

The GPH (Geweke and Porter-Hudak) fractional integration parameter (m = 62)

Estimate of fractional integration parameter = **0.0419757** (0.105919)

Test statistics: t(60) = 0.396298, p-value 0.6933

The Whittle local estimator (m = 62)

Estimate of fractional integration parameter = **0.0407482** (0.0635001)

Test statistics: z = 0.641704, p-value 0.5211

Period 4:the rest of sample (observations 3073–4433)

The GPH (Geweke and Porter-Hudak) fractional integration parameter (m = 74)

Estimate of fractional integration parameter = **-0.016919** (0.0676012)

Test statistics: t(72) = -0.250277, p-value 0.8031

The Whittle local estimator (m = 74)

Estimate of fractional integration parameter = **-0.0135082** (0.0581238)

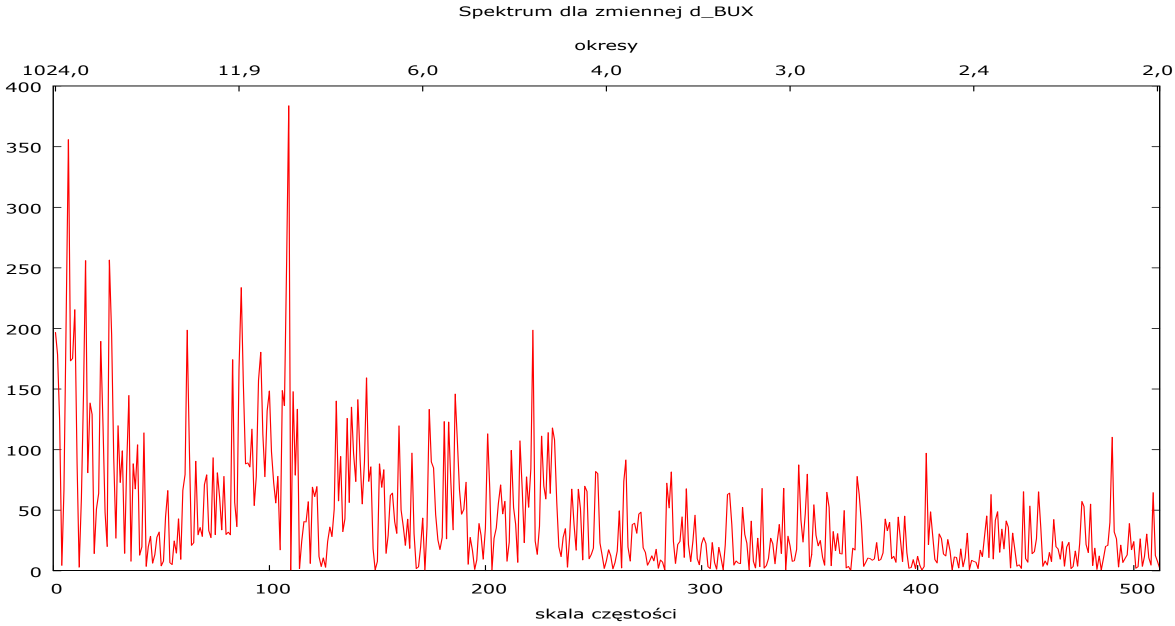
Test statistics: z = -0.232404, p-value 0.8162

Fractional integration parameter and the Hurst exponent fulfill condition $d = H - 0.5$. According to aforementioned classification, $d = 0$ corresponds to a stationary process, $d < 0$ to an antipersistent process, and positive values less than 0.5 – to a stationary process with long memory.

Our results allow us to formulate a conjecture: during first and second part of analyzed period, the BUX returns are characterized by trend persistence (this part of sample corresponds to periods of growth of index value), later fractional integration parameter is close to zero, in last part of sample the returns series is antipersistent, which is shown in more often changes of sign (see fig. 2, showing increase in volatility of a series). This last part of sample covers period of crisis for the Hungarian economy, hence increase of risk – perceived by investors – described as increase of volatility, is quite understandable.

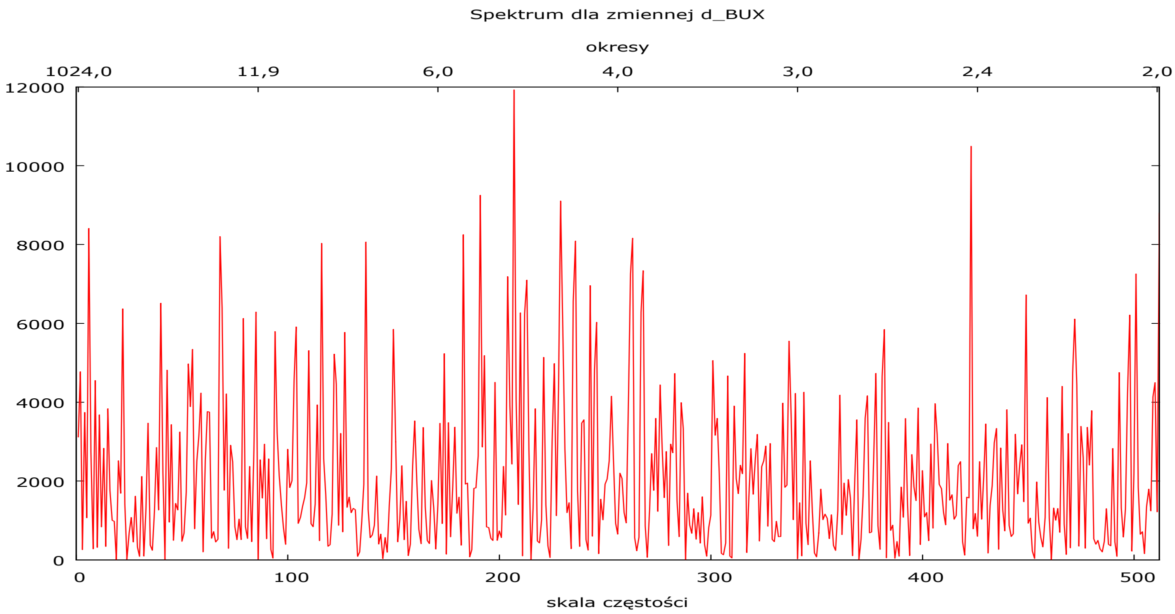
Fig. 6a,b,c,d shows spectral density function of returns, for the four subsamples respectively. This function is a representation of the series in frequency domain. Local maxima of this function occur for frequencies ω corresponding to cyclical fluctuations of respective period $T = 1/\omega$. Note values on vertical scale – we can see that spectral density function for the BUX returns has higher values toward the end of sample, which means that the series is more volatile near the end of sample.

FIGURE 6a. Spectral density for logarithmic returns – first 1024 observations



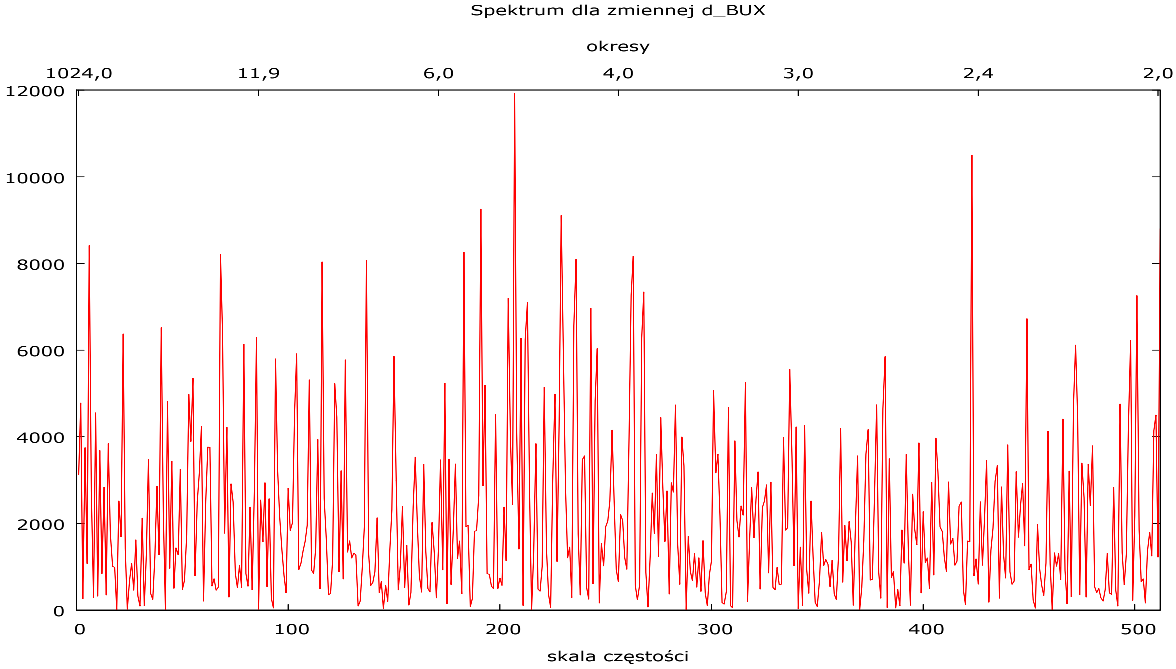
Source: own computations

FIGURE 6b. Spectrum for logarithmic returns, sample 1025-2048.



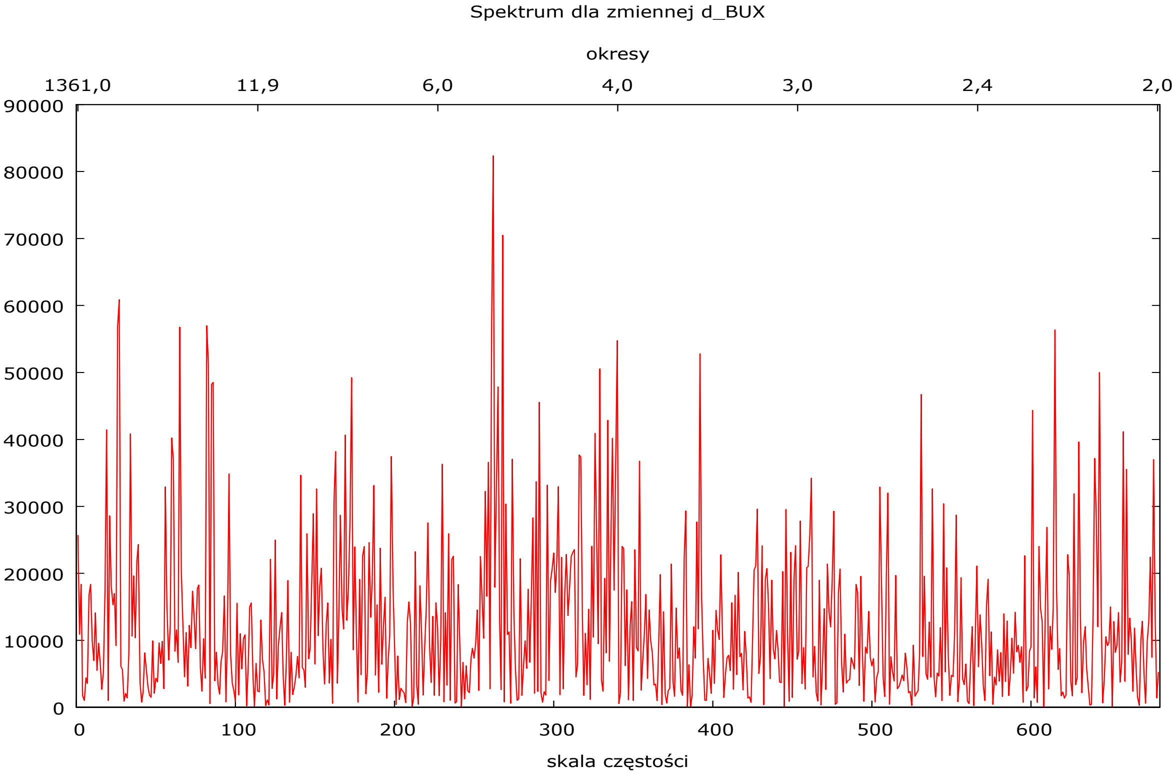
Source: own computations

FIGURE 6c. Spectrum for logarithmic returns, sample 2049-3072.



Source: own computations

FIGURE 6d. Spectrum of logarithmic returns, sample 3072-4433.



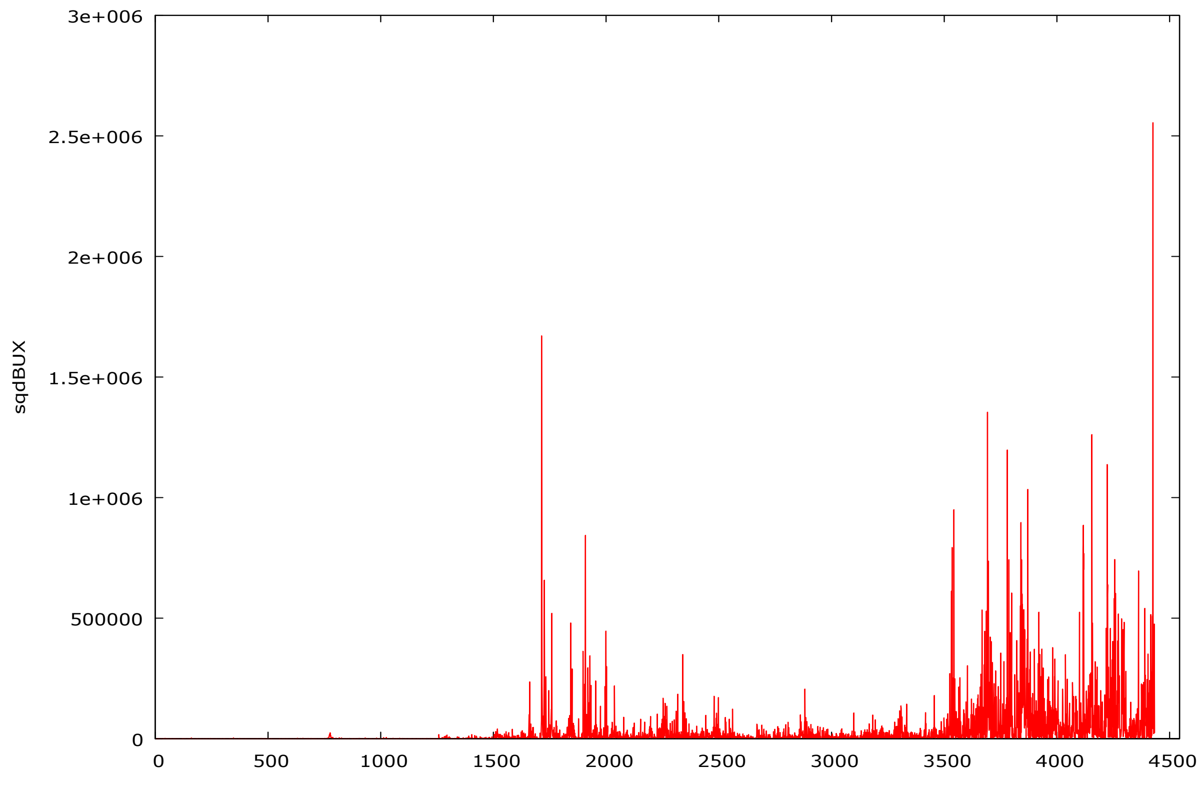
Source: own computations

6. Squared returns of the BUX index

For investors an important feature of a financial instrument is the risk involved. This risk can be measured with variance of a series, conditional variance with respect to a set of information available at time *t.* This kind of measure is based on squared returns for the series. Variance and sum of squared returns are measures of volatility of the series. Hence we check behavior of squared returns for the BUX index, their particular characteristics, periodograms and results of tests.

Figure 7 shows squared returns of the BUX index. The amplitude of changes is especially high for observations with numbers higher than 1700 – note huge increase of value for observations since 3500 up to the end of sample.

FIGURE 7. Squared returns of the BUX index



Source: own computations

Increase in value of squared returns, especially to the end of sample, means that volatility in several subperiods behaves differently. Value is especially high for 1716 observation (and equal to 1670660), for 3692 observation (equal to 1353779), 3870 observation (equal to 1033720), 4155 observation (equal to 1260747), 4223 observation (equal to 1136953), 4426 observation (and equal to 2554627).

To analyse squared returns we can also use fractional integration parameter estimates. According to C. M. Hurvich and B.K. Ray [2003], the local semiparametric Whittle estimator applied to periodogram of squared returns has lower bias, and estimates errors for samples with smaller number of observations give more accurate confidence intervals than for the Geweke and Porter-Hudak [1983] method.

The GPH test and Whittle estimator, applied to the whole sample of squared returns, give the following estimates of fractional integration parameter: 0.3396 and 0.37962, respectively. Probability of obtaining such a value under the null of d =0, is low (with p-value 0.06), hence the null is to be rejected.

Value of fractional integration parameter equal to 0.34-0.38 mean not only that the series is stationary and results of external shocks diminish with time, but also that there is long memory of the process.

Let us compute estimates of the fractional integration parameter of *squared* returns for the same four subperiods of approx. one thousand observations as previously. Results are as follows.

Period 1:

The GPH (Geweke and Porter-Hudak) fractional integration parameter (m = 63)

Estimate of fractional integration parameter = **0.272431** (0.0196243)

Test statistics: t(61) = 13,8823, p-value 0.0000

The Whittle local estimator (m = 63)

Estimate of fractional integration parameter = **0.277216** (0.0629941)

Test statistics: z = 4.40066, p-value 0.0000

Period 2:

The GPH (Geweke and Porter-Hudak) fractional integration parameter (m = 62)

Estimate of fractional integration parameter = **0.38845** (0.0783104)

Test statistics: t(60) = 4.96039, p-value 0.0000

The Whittle local estimator (m = 62)

Estimate of fractional integration parameter = **0.367896** (0.0635001)

Test statistics: z = 5.79363, p-value 0.0000

Period 3:

The GPH (Geweke and Porter-Hudak) fractional integration parameter (m = 63)

Estimate of fractional integration parameter = 0.358916 (0.0892315)

Test statistics: t(61) = 4.0223, p-value 0.0002

The Whittle local estimator (m = 63)

Estimate of fractional integration parameter = **0.315125** (0.0629941)

Test statistics: z = 5.00246, p-value 0.0000

Period 4:

The GPH (Geweke and Porter-Hudak) fractional integration parameter (m = 74)

Estimate of fractional integration parameter = 0.344771 (0.0909134)

Test statistics: t(72) = 3.7923, p-value 0.0003

The Whittle local estimator (m = 74)

Estimate of fractional integration parameter = 0.371791 (0.0581238)

Test statistics: z = 6.39653, p-value 0.0000

Estimates of the fractional integration parameter for *squared* returns behave differently than for *returns* of the series. In *all cases* the value of *d* is in interval between 0 and 0.5, which signals long memory in a series. The Hurst exponent for squared returns of the BUX index is 0.86, and that means that the series is nonstationary.

7. ARCH effect for the BUX returns

To check whether there is an ARCH effect for the BUX index returns, we next estimate an AR model for squared returns. The Engle test of the ARCH effect is constructed as test of joint significance of all lagged squares parameters (without an intercept). If we reject joint significance, there is an ARCH effect, hence it is possible to estimate model with conditional heteroskedasticity and use it to forecast the series. The procedure is as follows. We estimate regression of the form

$$r_t^2 = \beta_0 + \beta_1 r_{t-1}^2 + \beta_2 r_{t-2}^2 + ...\beta_k r_{t-k}^2 + \varepsilon_t$$

The null of no ARCH effect corresponds to assumption of insignificance of lagged variables parameters: $\beta_i = 0$ for all i = 1, 2,…, k, where k is number of lags. Results of corresponding regression (with lags up to 4) are as follows (see table 5). Computed value of statistics for the joint significance of β_i equals 828.55 and is higher than a critical value in tables of chi-squared distribution. The null of no ARCH effect is hence rejected.

TABLE 5. Estimation of the ARCH test regression

Variable	Estimate	Error	*t*-Statistics	P-value
Constant	30769.2	3315.86	9.279	<0.00001 ***
beta_1	0.175090	0.0148992	11.752	<0.00001 ***
beta_2	0.165736	0.0150555	11.008	<0.00001 ***
beta_3	0.121145	0.0150240	8.063	<0.00001 ***
beta_4	0.120043	0.0149262	8.042	<0.00001 ***

Source: own computations

8. Correlogram of squared returns

One measure of volatility of a series is sum of squared returns. The correlogram for squared returns of the BUX index – empirical ACF and PACF function and values of the Ljung-Box statistics – unambiguously indicate that correlation coefficients and partial correlation coefficients are significant (we computed sample PACF and ACF up to 24 lags, and the values are greater than critical value). The graph of PACF may indicate some cyclical changes – values of PACF are somewhat greater for 6th, 12th, 18th, 24th etc. lags than for other values. This might be a result of weekly seasonality.

TABLE 6. Empirical functions ACF, PACF and the Ljung-Box test for squared returns

Lags	ACF	PACF	Ljung-Box Q
1	0.2876 ***	0.2876 ***	366.8231
2	0.2841 ***	0.2195 ***	724.7679
3	0.2525 ***	0.1439 ***	1007.6778
4	0.2451 ***	0.1191 ***	1274.1929
5	0.2091 ***	0.0662 ***	1468.3006
6	0.2560 ***	0.1252 ***	1759.1743
7	0.1843 ***	0.0228	1909.9761
8	0.1916 ***	0.0411 ***	2073.0358
9	0.1842 ***	0.0402 ***	2223.7593
10	0.2183 ***	0.0826 ***	2435.5343
11	0.1866 ***	0.0375 **	2590.3233
12	0.2474 ***	0.1055 ***	2862.5047

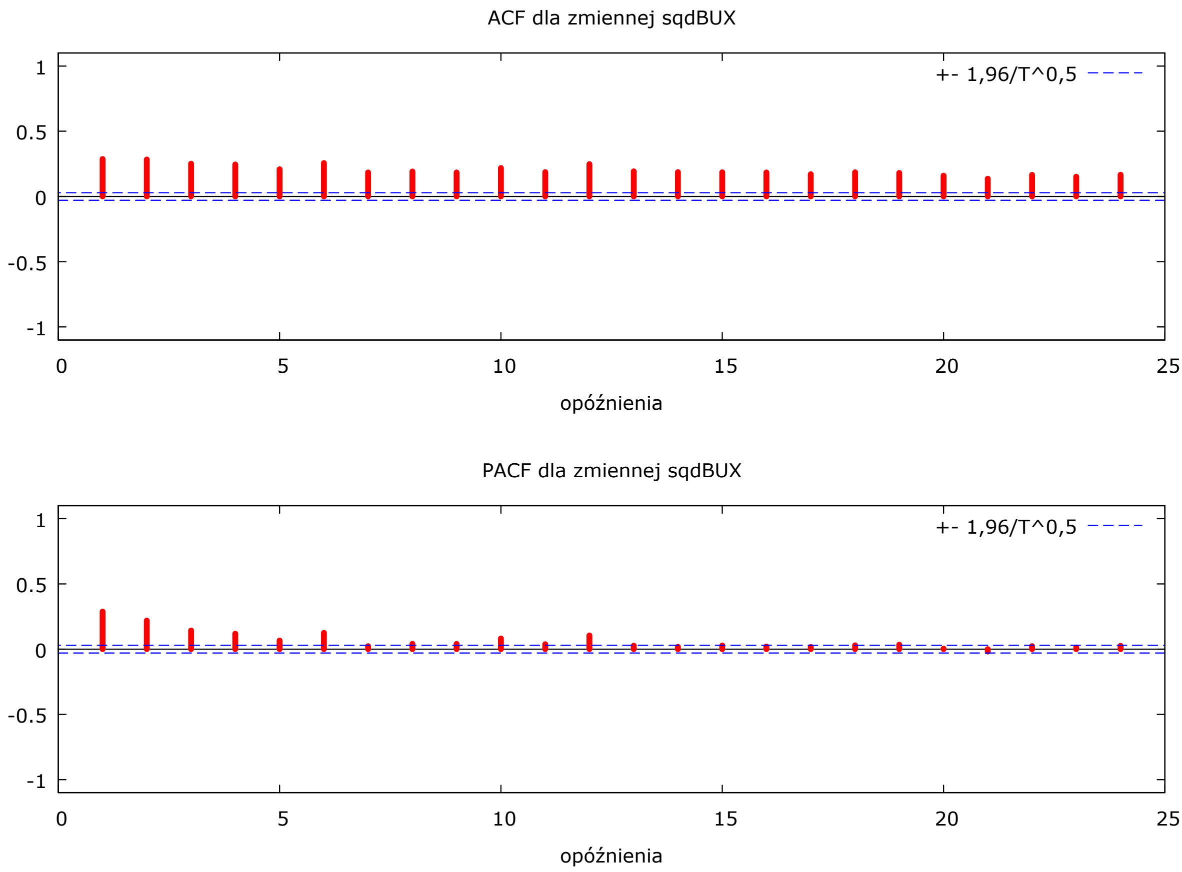
Lags	ACF	PACF	Ljung-Box Q
13	0.1925 ***	0.0276 *	3027.2259
14	0.1873 ***	0.0190	3183.2142
15	0.1862 ***	0.0280 *	3337.4741
16	0.1850 ***	0.0213	3489.7816
17	0.1706 ***	0.0175	3619.3587
18	0.1863 ***	0.0293 *	3773.9155
19	0.1805 ***	0.0339 **	3919.0214
20	0.1601 ***	0.0035	4033.1705
21	0.1366 ***	-0.0182	4116.3570
22	0.1661 ***	0.0236	4239.2344
23	0.1528 ***	0.0138	4343.3385
24	0.1678 ***	0.0256 *	4468.9273

Source: own computations

Computed values of the Ljung-Box test statistics are much higher than the critical values – hence the null hypothesis of joint insignificance of autocorrelation coefficients has to be rejected. Fig. 8 shows graphs of the ACF and PACF functions for the whole sample.

We compute now sum of squared returns for the first 1700 observations – mean of sum of squares is 3022.4 (median 51.7). For observations 1701-3500 average is 18288 (median 5458.3). For observations from 3501 to the end of sample mean equals $1.0505 \cdot 10^{15}$. Hence volatility of index and differences of behavior can be easily seen.

FIGURE 8. The ACF and PACF for squared returns of the BUX index, whole sample



Source: own computations.

9. Summary

Based on results presented, we can formulate the following conjectures, and ideas for future research:

1. Nonstationarity and stationarity tests (augmented Dickey-Fuller and KPSS test) show that the BUX quotes series is nonstationary, and logarithmic returns are stationary.
2. The autocorrelation and partial autocorrelation functions for the BUX index and the Ljung-Box test statistics show that behavior of the series is typical for financial instruments, i.e., is characterized by long-memory (seen in slow decrease of correlation coefficient in time).
3. Sample autocorrelation function shows that correlations are much weaker for the returns than for the original series.
4. More accurate signals of long memory of the series can be seen in estimates of fractional integration parameter and estimates of the Hurst exponent. For the most part of sample,

returns of the BUX index tend to maintain trend, this corresponds to periods of growth of the original index. Later fractional integration parameter for returns is close to zero, and in the last period (year 2008) the series is antipersistent, which results in more often changes of returns signs.

5. Graphical analysis of squared returns shows that volatility of index quotes tends to be higher close to the end of sample, which agrees with results of 4. Increase of volatility and amplitude suggests also increase of risk, especially towards the end of sample.
6. The ACF and PACF function for squared returns of the BUX index clearly show that there are significant dependencies. This has been confirmed by the Engle ARCH effect test: the null of no ARCH effect is rejected at 5%. This shows that analysis and forecasting of the BUX returns might be possible with use of ARCH type model.

10. Conclusions

The united Europe tends to support Hungary in its effort toward stabilization of economics and decrease of the current financial crisis results. At the end of October 2008 European Central Bank made an agreement with the Hungarian central bank of lending 5 bln Euro. This information caused slight decrease of slide on the Budapest stock exchange.

In October/November 2008 IMF, World Bank and European Union provided financial help of 20 bln Euro to the Hungary. According to then the Prime Minister Ferenc Gyurcsanyi's letter to IMF, this has helped to stabilize budget (the Hungarian banks at that time already obtained the first part of lend, equal to 2 bln 300 mln Euro). Nevertheless fight against crisis results in his opinion would be long and painful.

In spite of such an external help, Hungary did not regain trust of foreign investors (see Gazeta.pl on 7th November 2008) – decreases of the stock exchange rate index and prices of other instruments were equal to a dozen or so percents. Moody's rating agency downgraded rating for Hungary from stable to negative and at the same time rating of government bonds from A2 to A3. The IMF promised to lend Hungary 12,3 bln Euro. In spite of the crisis, Hungary have announced its wish to join Euro area as soon as possible, in order to stabilize the economy, decrease risk and improve foreign investors attitude. Later events have shown that those measures and announcements did not bring desired results, partly due to the global crisis.

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