THE LONG MEMORY PROPERTY OF HUNGARIAN MARKET PIG PRICES: A COMPARISON OF THREE DIFFERENT METHODS

SÁNDOR KOVÁCS, PRASERT CHAITIP, CHUKIAT CHAIBOONSRI, PÉTER BALOGH *

ABSTRACT: *The present study investigates the long memory property of market pig prices. Simply knowing that these time series have long term dependence could have strong significance when forecasting prices. The presence of long memory is crucial information in making business decisions and creating portfolios. Long memory can be measured by calculating the so-called Hurst exponent. In our article, we studied and described three different methods (Rescaled range, Detrended Fluctuation Analysis, Autoregressive Fractionally Integrated Moving Average). Data consist of four time series (piglet, young pig, sow, slaughter pig) between 1991 and 2011. Before conducting the econometric analysis, all the series were seasonally adjusted using the TRAMO/SEATS method. Data preparation was followed by differencing the time series and testing their normality and stationarity. In the next step, we divided the analysed period into four parts and determined the Hurst exponent for each sub-period, using all three methods. In summary, results showed that slaughter pig prices are random; pig and piglet prices developed similarly and have long memory, while sow price changes definitely have short memory. Among the methods of pinpointing long term memory, ARFIMA was used for making the forecast. The forecasting ability of the method was compared to the traditional ARIMA model, with ARFIMA proving to be the better of the two.*

KEY WORDS: *long memory property; market pig price; ARIMA model; ARFIMA model; DFA-2 method.*

JEL CLASSIFICATION: *C53; Q11.*

* *Assist. Prof., Ph.D., University of Debrecen, Hungary, kovacss@agr.unideb.hu*
Prof., Ph.D., Chiang Mai University, Thailand, webadmin@econ.cmu.ac.th
Assoc. Prof., Ph.D., Chiang Mai University, Thailand, chukiat1973@yahoo.com
Assoc. Prof., Ph.D., University of Debrecen, Hungary, baloghp@agr.unideb.hu

1. INTRODUCTION

Random movement is known as the Brown-motion or the random walk in the literature. In the case of a time series, this means that price movements from one period to another are random, irrespective of their direction (increase, decrease). In fact, the measurement of their increase or decrease, as that of the direction of their movements, is also random.

Previous research findings have substantiated how many systems in nature do not behave like a random movement, even if such behaviour were to be expected of them. This statement had been proved to many natural phenomena, such as river floods or rainfall, by Herold E. Hurst, an English hydrologist who investigated the changing water levels of the Nile (Hurst, 1952). Hurst arrived to the conclusion that some time series have a so-called long memory property, which means that a previous event, action or shock will have an influence on the far future.

Within the scope of this study, we test the Long Memory property on the monthly average pig market prices, including pigs, piglets, sows and slaughter pigs. We also calculate the Hurst exponent using three different methods in each time series. The Hurst exponent estimates the predictability of a time series and that is what makes this statistical tool valuable in financial analysis and this is also the reason we chose to use it.

2. THE LONG MEMORY PROPERTY

A stationary time series has the Long Memory property if the autocorrelation function decays to zero very slowly over a very long time period. The rate of decay is determined by the so-called Hurst exponent (H) according to the following expression (Beran, 1994):

$$\rho(k) = Ck^{-\alpha} \text{ , where H = 1-}\alpha/2, \tag{1}$$

while C is a finite constant and $\rho(k)$ is the autocorrelation function of the time series with lag k. According to Hurst's conclusions, if H=0.5 than data points of the time series are independent and the series is a random walk.

If $0.5<H<1$, the series indicates persistent behaviour or long memory. If there is an increase from time step t_{i-1} to t_i there will be probably be an increase from t_i to t_{i+1} (Alptekin, 2006). The same is true for decreases. A decrease will tend to follow a decrease, while an increase will tend to follow an increase. The autocorrelation function of such series is always positive.

When the Hurst exponent is positive and below 0.5, then the series is called anti-persistent. In this case, an increase will tend to be followed by a decrease or a decrease will be followed by an increase (Alptekin, 2006). The autocorrelation function of these types of series is negative. This behaviour is sometimes called mean or trend reversion, as a low H value indicates that the process could not diverge significantly from the seasonal trends and the effect of the reversions is strong.

The Hurst exponent has already been employed in many fields in mathematics, such as chaos theory and fractal analysis (Mandelbrot, 1969). As the theory of fractals has been developed, the methods for calculating the Hurst exponent have become widely used.

2.1. Major application fields

The Long Memory property of time series has been a focus of attention in recent years and applied mainly to describe stock prices in financial and economic literature (Lo, 1991; Chow et al., 1995; Eisler, 2007; Erfani-Samimi, 2009; Telcs, 2009). Additionally, other authors have studied the inflation rate (Scacciavillani, 1994; Hassler-Wolters, 1995), the price movements of gold (Cheung-Lai, 1993) and the fluctuation in exchange rates (Booth et al., 1982; Fang et al., 1994; Alptekin, 2006). Research findings uniformly confirm that investigating the long term dependence in time series plays a huge rule in determining price movements and in making more precise forecasts. On the other hand, the strength of the Long Memory and the length of the time period is crucial information in making business decisions and creating portfolios. Some applications in the literature deal with the fluctuations in commodity futures prices (especially crude oil, coffee, sugar, maize, wheat, soybean, swine, cattle) (Helms et al., 1984; Tomek, 1994; Kohzadi et al., 1996; Wei-Leuthold, 2000; Shahwan-Odening, 2007; Ramirez et al., 2008; Ahti, 2009; Power- Turvey, 2010).

3. DATA AND APPLIED METHODS

For the examination of long term memory, three main methods can be applied for calculating the H-exponent:

- Rescaled range (R/S)
- Detrended Fluctuation Analysis (DFA)
- Autoregressive Fractionally Integrated Moving Average (ARFIMA)

The first method deals with the question whether the time series has long term memory or not, the third method examines how strong the long term memory of the time series is and whether this method can be used to make forecasts. The advantage of the second method is that it can be applied with non-stationary time series and is capable for being used in the measurement of fluctuations. All three methods can be applied in substitution of any of the other methods because they each provide information which the others do not. Agricultural prices often show irregular behaviour, which refers to the nonlinear interdependency of the markets. The nonlinear interdependency in economics is not a specified concept in the literature. References do exist, but only in relation to, i.e. the following phenomena: the distribution of prices is usually non-normal; the autocorrelations of time series, even in cases of long time periods, are long term dependences; the time series includes non-periodical cycles and is not stationary. The long term time series involve the above- mentioned characteristics; therefore, the examination of long term memory is capable of characterising all these phenomena.

3.1. The Rescaled range (R/S) method

Among the methods capable of being employed in the examination of long term memory, the rescaled range is the most widely used and is one of the methods with the least estimation errors (Hurst, 1951). First, he applied the maximum values x_i of subsequent years, according to the formula (2) (Telcs, 2009):

$$Y_i = \sum_{j=1}^{i} x_j \tag{2}$$

Then he computed deviation of the k-th sum from the “n” years average:

$$D_k = Y_k - \frac{k}{n} Y_n \tag{3}$$

If D_k is positive the higher (above the average) years dominate.

Hurst also computed the [Max(Di) – Min(Di)] = Rn values and divided with the empirical deviation. The quotient can be given according to formula (4) (Alptekin, 2006):

$$\frac{R_n}{S_n} \cong C \cdot n^H \tag{4}$$

When analysing the water level of the Nile, Hurst got 0.7 for the quotient of the formula (4) (Telcs, 2009).

3.2 The estimation of Hurst exponent by means of the R/S method

In the first step, we divide the time axes consisting of N data into m continuous part periods, in which there is N data (N=n*m). We calculate the R/S statistics in the following way (Alptekin, 2006):

$$\left(\frac{R}{S}\right)_j = s_j^{-1}\left[\max_{1\le k\le n} \sum_{i=1}^{k}\left(X_{ij}-\overline{X}_j\right) - \min_{1\le k\le n} \sum_{i=1}^{k}\left(X_{ij}-\overline{X}_j\right)\right], \tag{5}$$

where s_j is the standard deviation of the j*th* period, the X_{ij} is the i*th* data of the j*th* period.

It is necessary to rescale the volume, because this way, different periods can be compared. In the second step, we calculate with a given n and m the following statistics (Alptekin, 2006):

$$\left(\frac{R}{S}\right)_n = \frac{1}{m}\sum_{j=1}^{m}\left(\frac{R}{S}\right)_j \tag{6}$$

We repeat the first two steps in a way that we increase n to n/2 and we divide the time axes only for two part intervals. The Hurst exponent can be given by using a regression estimation according to formula (7):

$$\log\left(\frac{R}{S}\right)_n = \log(C) + H\log(n) \tag{7}$$

The (7) formula is the logarithmic version of formula (4) which describes the R/S values according to time in a logarithmic frame of reference. The Hurst exponent is given by the gradient of the diagram. With the H parameter estimated by the R/S method, we can give the average length of non-periodical cycles, i.e. the average length of long term memory. For the different values, we calculate the R/S values and the H values and observe that the H values with which n value reach there apex. This n value is the average length of non-periodical cycles.

3.3. Detrended Fluctuation Analysis (DFA)

The basis of DFA was established by Peng et al. (1992) and was called fluctuation analysis. It was first developed for studying DNA-sequences and nucleotides (Peng et al., 1993; Peng et al., 1994). DFA is a somewhat different from the fluctuation analysis, in that it removes the local trends in the series. The first application was also presented by Peng et al. (1994) and Peng et al. (1995).

Let us suppose that we have a time series (x_i) of N elements measured at regular intervals and the elements of the series follow random movement around the mean. The trajectories of the time series are computed as follows (Király, 2005):

$$y(j) = \sum_{i=1}^{j} x_i \text{ (j=1,...,N)} \tag{8}$$

Expression 8 gives the sum of the elements at time point j. The trajectories will then be split into n-length parts (time windows), so the maximum number of the sections is $\left[\frac{N}{n}\right]$. The local trends denoted by $f_k^p(j)$ polynomial are estimated in every time window, where j is the actual time point, p is the degree of the polynomial and k is sequential number of the actual time window.

In the next step the detrended $z_p(j)$ data are generated according to equation 8:

$$z_p(j) = y(j) - f_k^p(j) \text{ (j=1,…,N)} \tag{9}$$

Given the length of the time window, the average square fluctuation can be measured in the following way (Peng et al., 1993; Peng et al., 1994; Király, 2005):

$$F_p(n) = \frac{1}{n \cdot \left[\frac{N}{n}\right]} \cdot \sqrt{\sum_{j=1}^{n \cdot \left[\frac{N}{n}\right]} z_p^2(j)} \quad (10)$$

In the case of long range dependence, we suppose that $F_p(n)$ is the power of n with the DFA-p exponent δ /$F_p(n) \approx n^{\delta}$/. Short-range dependent time series have δ=0.5, long-range dependent series and are characterized by a $\delta > 0.5$, while anti-persistent series have $\delta < 0.5$ (Koscielny-Bunde et al., 1998; Talkner-Weber, 2000; Király, 2005).

3.4 ARFIMA models

The fractionally integrated ARIMA model was created by Granger and Joyeux (1980) and Hosking (1981). This model counts as a parametrical method in revealing long term memory and its basis is an ARIMA model return with the help of a lag-operator in formula

$$\left(1-\sum_{i=1}^{p}\varphi_i L^i\right)(1-L)^d X_t = \left(1+\sum_{i=1}^{q}\theta_i L^i\right)\varepsilon_t \text{, ahol } L^i X_t = X_{t-i} \quad (11)$$

The d parameter means the degree of differentiation and in the case of d=0 we get a stationary time series and in the case of d=1 the time series is non-stationary. There are stationary time series in the case, of which the autocorrelation formula depends on long range and there is correlation between two further observations, as well. In this case, there can be two cases. 1. The time series involves unit root, but the unit root test shows a false result. 2. In the time series there is not unit root, but it has long term memory; therefore, the traditional ARIMA model does not fit. In the case where we differentiate the time series again, this would not be a solution either, because of over-differentiation. Granger and Joyeux (1980), and Hosking (1981) suggested as a solution that the d differentiating parameters have a fractional value. In this way, the Taylor series of the $(1-L)^d$ difference operator in the formula of the ARIMA model is given according to formula (13) (Korkmaz et al., 2009):

$$(1-L)^d = 1 - dL + \frac{d(1-d)}{2!}L^2 - \frac{d(1-d)(2-d)}{3!}L^3 + \ldots(-1)^k \frac{d(1-d)(2-d)\ldots(k-1-d)}{k!}L^k \quad (12)$$

In other words, fraction differentiation is given by an indefinite autoregressive representation of the time series, with integer lags which have special coefficients.

If the value of d is between 0 and 0.5, the time series has long term memory, if d<0, it has short term memory. If d=0, the process is random walking. Therefore, if we add 0.5 to the d parameter, we get the estimation of the Hurst exponent.

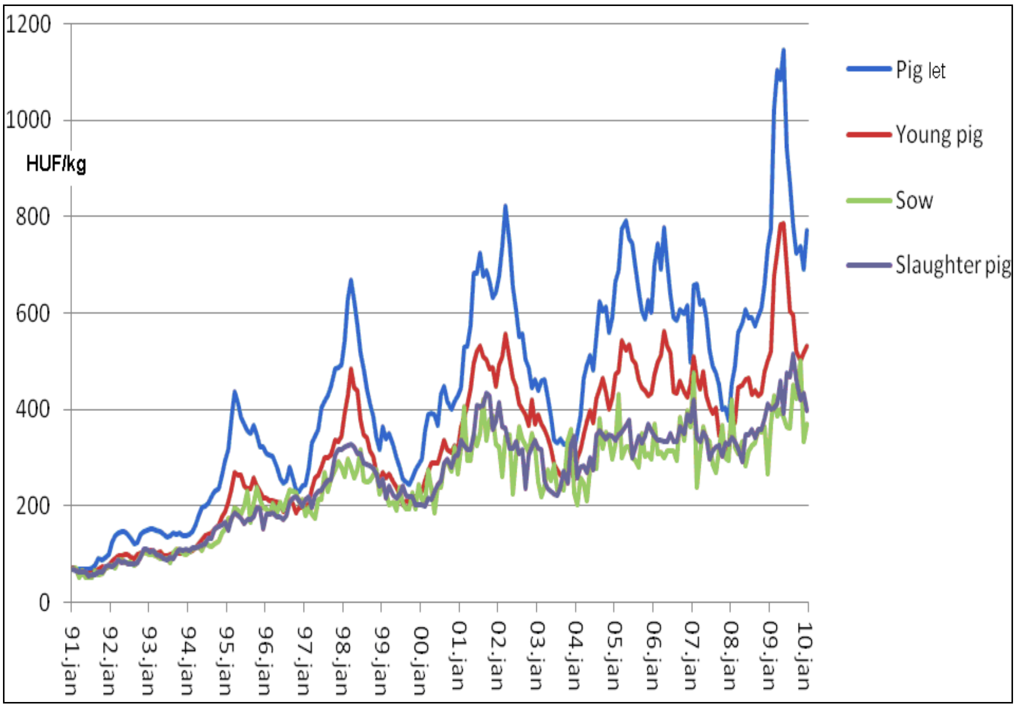
4. RESULTS

A significant part of the studies analysing the pig sector mentions that the emission of the sector and the prices are described by cyclical movements. Nyárs (2005) thoroughly analysed the significant pig-keeping member states of the EU and the characteristic processes of the Hungarian and Polish pig sectors and stated that, in the examined states, pig cycles could be revealed inthe buying up prices. The experts on the regulation of market processes have been examining formation price oscillations and the pig cycle for decades. The theory of the cobweb model can be found in classic economic literature. This theory posits the notion that the loss of market information has an effect on the behaviour of the cycle. The price of slaughter pig, crop prices compared to each other have a significant effect on the decisions of pig-keepers, particularly in reference to the activities of small-scale producers. The formations of Hungarian buying-up prices are described by shorter cycles than those EU member states with advanced pig-keeping methods. In the EU, there are 9 year periods, while in Hungary, 3 or 4-year-periods are repeated. The reason for the long cycles is, on the one hand, the predictable market regulation and, on the other hand, the concentrated production structure. Therefore, we chose the monthly average Hungarian market prices of the period following 1990 as a basis of our examinations. The observed prices were as follows: the average price of piglets, young pigs, sows and slaughter pigs at animal markets and fairs. For the empirical analysis, 240 observations in all the four categories, i.e. the monthly average market prices observed between January 1991 and December 2010, were at our disposal.

4.1. The monthly formation of seasonally adjusted market pig price data between January 1991 and December 2010

Before examining the time series economically, we must filter out the season effects. The time series we used involves 20 entire years and did not contain missing observations. Before starting the econometric analysis, we adjusted the series seasonally by using TRAMO/SEATS (Golinelli–Parigi, 2008). We applied a trading day adjustment (5 day and length of month effect) and an Easter adjustment only in cases where such adjustment was significant. We also detected the additive outliers, the temporary changes and the level shifts automatically. For our additional investigations, we used the adjusted series and Figure 1 also presents the seasonally adjusted series.

Figure 1 shows that during the period since 1990, the basic trend in pig market prices has been slightly increasing. The market is still basically a buyer's market (Bakucs-Fertő, 2005) which affects the development of the prices, apart from seasonal and cyclical effects. In each case, the average prices have changed according to a 3-year cycle, which has turned into a 4-year cycle since Hungary joined the EU. Price developments show a large fluctuation over the 20 years since 1990, so we had to divide the entiree period into 4 sub-periods from a professional standpoint and analyse the four series even in these sub-periods. The first part contains data from 1991 to 1994, as prices were almost continuously increasing, without any cyclical affect. The second part involves data from 1995 to 2004. In this period, there was experienced a large cyclical effect, which caused a 3-year movement in prices. It is also observable that slaughter pig prices and sow prices developed the same way.



Remark: The seasonal adjustment was used by the TRAMO/SEATS-program.
Source: Magyar Statisztikai Évkönyv [1991 - 2006] and KSH stAdat táblák (2010).

Figure 1. Seasonally adjusted monthly average pig prices /1991- 2010/ (in HUF/kg)

The third period covers the first stage after EU accession, during which prices either decreased or stagnated. There had been a dramatic decrease in the cases of pig and piglet prices. The final sub-period, as a second stage after EU accession, lasts from July 2008 to December 2010. In this stage, we can observe a steady increase in pig and piglet market prices, while slaughter pig prices increased modestly (Figure 1) and sow prices follow a random movement.

4.2. Economic analysis of the data

Long memory is not a clearly specified concept in the financial theory. What is present in the literature are symptoms suggesting long memory, i.e. that prices are usually distributed non-normally; the autocorrelation function decays to zero very slowly, even for a very large period; the series has non-periodic cycles and is not stationary (Taylor, 1986). According to these symptoms, we would further test the seasonally adjusted time series, in order to find more evidence of long memory.

Table 1. Normality test results of the seasonal adjusted time series

Tests	Sow	Piglet	Young pig	Slaughter pig
Doornik-Hansen*	9.168 (0.010)	7.985 (0.018)	12.155 (0.002)	15.227 (0.000)
Shapiro-Wilk	0.969 (0.000)	0.969 (0.000)	0.965 (0.000)	0.959 (0.000)
Lilliefors**	0.085 (0.000)	0.062 (0.030)	0.075 (0.000)	0.114 (0.000)
Jarque-Bera	6.296 (0.043)	8.26 (0.016)	8.799 (0.012)	9.229 (0.010)

Remark: Econometric Software GRETL was used to test normality, significances are in parenthesis
**Doornik and Hansen (2008);*
*** Lilliefors (1967)*

The normality and stationarity of the series were tested, as well as the decay of their autocorrelation function. Long memory processes exhibit non-normality and non-stationarity, their autocorrelation function decays to zero very slowly. Normality test results can be seen in Table 1.

The null hypothesis of the normality tests is that data is normally distributed. All the tests proved significant at the 5% significance level, so we can reject the hypothesis of normality in each case.

Table 2. Stationarity test results of the seasonal adjusted time series by ADF-test

Model	Sow	Piglet	Young pig	Slaughter pig
Constant	-1.587 (0.488)	-2.39509 (0.1431)	-2.134 (0.231)	-1.547 (0.509)
Constant and trend	-3.274 (0.071)	-4.57618 (0.001)	-4.446 (0.001)	-2.962 (0.143)
Differentiated series	-10.917 (0.000)	-8.19323 (0.000)	-7.549 (0.000)	-7.544 (0.000)

Remark: Econometric Software GRETL was used to test normality; we employed the Augmented-Dickey-Fuller test; significances are in parenthesis

The null hypothesis of the ADF test is that the time series has a unit root, as the time series is non-stationary. The test proves non-stationarity in all cases, as the null hypothesis cannot be rejected at the 5% significance level Table 2. Pig and piglet market prices are trend stationary; the other series are not. On the other hand, the differenced series are all stationary, so it was reasonable to differentiate the seasonally adjusted series and apply the Hurst exponent estimations to them.

Table 3 includes the descriptive statistical indexes of differentiated price data. On this basis, it can be stated that for the whole time serial, the average of the change in pig price was the highest 2.61 (HUF/kg), a result which could be connected with the fact that also the unit price was the highest here. The value of the median was quite the opposite, since for young pigs, 50% of the monthly changes were lower than 2.26 HUF/kg. The standard deviation was the most significant in the case of sow price changes. The minimum and maximum of changes could also be observed here (-244.99 and 201.39HUF/kg price change).

In Table 3, we included not only the characteristics of the whole time serial, but also the characteristics of each period. Similar to the fact observed in the whole time serial, the average of piglet price change was the highest except for the 3*rd* period. The value of the median fluctuated between 0 and 1 in the second period, while the other periods were characterised by higher fluctuation. It is interesting to observe that the value of standard deviations grows and, similar to the whole data serial, the average deviation was the highest in the case of sows in every serial. The formation of minimum values is related to this trend, since in the 3*rd* period, the smallest price difference between the two time points was -244.99 HUF/kg in the case of sows. This value shows how large the loss was which producers suffered month after month, if they were forced to sell their animals in the given period. In the case of maximum values, it can be stated that, except for the 4*th* period, the highest price movement between the two months appeared for piglets. Therefore, producers could earn their highest incomes by selling their piglets, if they exploited the advantages coming from the price change. Thus, on the basis of Table 3, it can be stated that the differentiated price data in the various periods showed a big difference in cases of certain products.

Table 3. Descriptive statistical values of the differentiated price data

Me.: HUF/kg

Denomination	Piglet	Young pig	Sow	Slaughter pig
		Whole period		
Mean	***2.61***	1.76	1.40	1.36
Median	0.82	***2.26***	0.54	1.29
Standard Deviation	35.32	23.16	***49.94***	24.02
Minimum	-156.76	-86.07	***-244.99***	-86.51
Maximum	144.37	149.74	***201.39***	84.08
		First period		
Mean	***4.97***	2.68	1.78	2.08
Median	3.09	2.91	1.25	1.19
Standard Deviation	10.23	5.93	8.03	6.66
Minimum	-10.34	-14.29	-16.08	-8.61
Maximum	***32.33***	19.35	19.99	20.96
		Second period		
Mean	***2.68***	2.18	1.21	1.49
Median	***0.15***	***0.76***	***0.15***	***0.69***
Standard Deviation	30.86	21.08	42.57	25.30
Minimum	-58.76	-51.48	-128.23	-86.51
Maximum	***123.02***	65.00	103.62	77.96
		Third period		
Mean	-1.38	-0.23	0.44	0.06
Median	-1.42	2.01	-3.18	0.44

Standard Deviation	50.22	24.31	66.01	25.82
Minimum	-156.76	-61.72	***-244.99***	-75.65
Maximum	***130.68***	39.08	128.75	55.67
		Fourth period		
Mean	***4.20***	1.42	2.90	1.52
Median	-6.05	1.84	7.09	5.56
Standard Deviation	***50.65***	***40.95***	***82.24***	***33.04***
Minimum	-78.86	-86.07	-165.30	-71.07
Maximum	144.37	149.74	201.39	84.08

Source: Own calculation

Before we turn to the results of the estimations, one thing must be strongly emphasized. In the case H=0.5, the original data follows a random movement, as it is non-stationary. The differenced series (price change) is stationary, so it cannot follow a random movement.

Table 4. DFA-2* estimated Hurst exponents

Sub period	Sow	Piglet	Young pig	Slaughter pig
1.	0.639	0.765	0.459	0.824
2.	0.852	0.785	0.223	0.477
3.	0.397	0.555	0.256	0.497
4.	0.588	0.686	0.274	0.525
Whole period	0.750	0.709	0.162	0.402

**Remarks: Estimations were made by the DFA Software with p=2, quadratic polynomials were used for detrending the series*
(*PhysioNet* [2010])

Average sow market price changes have short memory in all sub-periods and in the whole period (Table 4). Slaughter pig price changes did not have long memory except in the first sub-period. The Hurst exponents of the pig and piglet price changes are very similar to each other, excepting the third sub-period in all other sub-periods and during the whole period, they had long memory. The slaughter pig price changes had short memory in the whole period, and the original prices show random movement in all sub-periods except the first one. These statements are greatly reflect those given in Figure 1.

Table 5. The Hurst exponents estimated by the R/S method

Period	Sow	Piglet	Young pig	Slaughter pig
1.	0.765	0.734	0.426	0.531
2.	0.657	0.659	0.354	0.525
3.	0.458	0.568	0.365	0.504
4.	0.849	0.669	0.287	0.582
Whole Period	0.484	0.487	0.280	0.419

Note: The estimation was made by the Rescaled range analysis program (*Sewell, 2010*)

The Hurst exponents estimated by the R/S method are the same as the values estimated by the DFA 2 method, except for some exceptions, as seen in Table 5. The exponent applying to the whole period and for young piglet prices and the value of the first period on the basis of the R/S method, in cases where slaughter pig prices refer to irregular movement. The changes of sow prices are short memory prices as it was shown by the DFA-2 method.

Table 6. Hurst exponents and model parameters estimated by the ARFIMA method

Period	Sow	Piglet	Young pig	Slaughter pig
1.	0.736 (p=3, q=2)	0.759 (p=2, q=2)	0.274 (p=3, q=2)	0.563 (p=1, q=4)
2.	0.863 (p=1, q=0)	0.652 (p=4, q=2)	0.174 (p=2, q=1)	0.392 (p=4, q=4)
3.	0.581 (p=2, q=3)	0.655 (p=3, q=2)	0.213 (p=4, q=4)	0.394 (p=1, q=1)
4.	0.869 (p=4, q=4)	0.773 (p=4, q=4)	0.317 (p=0, q=1)	0.459 (p=4, q=1)
Whole period	0.885 (p=4, q=3)	0.739 (p=1, q=0)	0.223 (p=4, q=3)	0.428 (p=3, q=4)

Note: The estimation was made by the Matrixer program (*Tsypalkov, 2004*).

The exponents estimated by the ARFIMA models are similar to the exponents estimated by the DFA-2 method and the same conclusions can be made except for the change of slaughter pig prices, as seen in Table 7. In the 2-4 periods, and also referring to the whole period, the exponents of slaughter pig price changes refer rather to short memory. In accordance with the findings given above, we would like to draw attention to the fact that one of the main advantages of the ARFIMA method is the definition of the strength of long term memory. All this can be observed in the analysis of the change of the piglet prices, where the parameters referring to the long term memory are higher than for the DFA-2 method in each period. In the case of young piglets, this is true only for the 3-4th and the whole period. Nevertheless, the parameters referring to short term memory in the case of sows in the first 3 periods are much lower than the values obtained using the DFA-2 method.

Among the methods of pinpointing long term memory, ARFIMA can be used for making forecasts. In Table 7, we have summarised the forecasting ability of the method compared to the traditional ARIMA model fitted for seasonally adjusted data. In the table, we compared the achievement of the two methods on the basis if the MAPE index. The mean absolute percentage error of the ARFIMA model turned out to be worst in the case of the forecast of the characteristically short term memory sow prices, while in the case of the characteristically long term memory piglet and mainly young piglet, this method was more efficient in forecasting. In the case of sows, for both methods, the MAPE index was significantly higher than 5%, since the changes in these prices show a much more hectic movement, compared to the other pig prices. Behind such a result could be the fact that the price of market sows is partly independent of breeding animal prices from the earlier periods. In the forecast of the slaughter pig prices, similar to random walking, the ARFIMA method was the more successful.

Table 7. The comparison of forcasts estimated by the ARFIMA and ARIMA methods on the basis of seasonally adjusted data

Time series	Model	Prices in 2010						MAPE*
		July	August	September	October	November	December	
Piglet prices	ARFIMA (5;0.485;3)	727.0	706.1	684.0	661.5	641.0	622.0	***3.367***
	ARIMA (4,1,4)	725.8	706.2	686.2	665.2	650.0	632.5	3.373
	Seasonally adjusted data	***724.4***	***709.9***	***704.6***	***654.0***	***614.6***	***698.3***	
Young pig prices	ARFIMA (1;0.085;0)	513.5	508.8	504.6	500.5	496.6	492.9	***1.786***
	ARIMA (2,1,2)	536.0	531.4	514.2	501.1	501.5	511.8	4.211
	Seasonally adjusted data	***504.9***	***492.2***	***508.1***	***497.3***	***476.5***	***492.5***	
Sow prices	ARFIMA (1;-0.1;1)	364.7	362.7	361.4	360.1	358.9	357.7	***19.009***
	ARIMA (0,1,1)	377.1	378.5	379.9	381.4	382.8	384.3	16.032
	Seasonally adjusted data	***429.8***	***325.9***	***527.2***	***445.0***	***486.1***	***401.4***	
Slaughter pig prices	ARFIMA (3;-0.011;4)	369.4	375.6	371.2	371.5	380.3	379.5	***2.894***
	ARIMA (3,1,4)	360.4	374.9	368.5	357.4	369.7	373.2	4.685
	Seasonally adjusted data	***400.9***	***372.9***	***374.3***	***379.3***	***390.3***	***392.5***	

Source: Own calculation with the help of the forecast and fracdiff packages of the R 2.11.1 program
** Mean Absolute Percentage Error*

4. CONCLUSIONS

On the basis of our analysis, it can be stated that the methods for the examination of long term memory exactly mirror the characteristics described for the specific periods of seasonally adjusted time series. During the examination of the changes in the piglet and young piglet prices, the DFA-2 and ARFIMA methods did not show long term memory in price changes, except as refers to the period (3rd period) after EU accession. In the same period, according to the R/S method and taking into consideration the whole serial, the piglet and young piglet prices showed irregular movement. In the case of sows, according to all three methods (DFA, R/S, ARFIMA), the changes in average market prices had a short term memory in each period and in total, as well. The explanation for this can be that the price of sows appearing on the market is partly independent of the breeding animal prices from the earlier periods. The changes of slaughter pig prices with the DFA and ARFIMA methods between 1991-1994 (first period) turned out to have a long term memory, which the R/S method did not show. The data of the original time series in the 2-4th periods are similar to random walking and the price changes in total have short term memory on the basis of the

DFA-2 and R/S methods. In the 2-4th periods and also in the whole period, the exponents of slaughter pig price changes refer to short memory, according to the ARFIMA method. Considering the comparison of the methods, the R/S method turned to be less robust in showing long turn memory in the cases of piglet and young pig price changes. Nevertheless, for these price changes, the other two methods obviously justified the existence of long memory. One of the main advantages of the ARFIMA method is in the definition of the strength of long turn memory, which could especially be observed in the analysis of piglet price changes, where the parameter values referring to long turn memory were higher in each period than the values at the DFA-2 method.

Therefore, in summary, slaughter pig prices are random; pig and piglet prices developed similarly and have long memory, while sow price changes definitely have short memory, which means that a decrease will probably be followed by a decrease in the long run. From among the methods capable of showing long turn memory, we tested the forecasting ability of the ARIMA method and compared it with the traditional ARIMA model fitted on the original data on the basis of the MAPE index. The mean absolute percentage error of the ARFIMA model turned out to be worse in forecasting sow prices with characteristically short term memory, while in cases of piglet and young pig prices with characteristically long turn memory, this method was the more efficient in forecasting.

REFERENCES:

[1]. Ahti, V. (2009) *Forecasting Commodity Prices with Nonlinear Models*, Discussion Paper No. 268, University of Helsinki, Helsinki, http://ethesis.helsinki.fi/julkaisut/eri/hecer/disc/268/forecast.pdf

[2]. Alptekin, N. (2006) *Long Memory Analysis of USD/TRL Exchange Rate*, International Journal of Social Sciences 1(2): 111-116

[3]. Bakucs, L.Z.; Fertő, I. (2005) *Marketing Margins and Price Transmission on the Hungarian Pork Meat Market*. Agribusiness. 21(2): 273–286

[4]. Beran, J. (1994) *Statistics for Long-Memory Processes,* Chapman and Hall Publishing Inc. New York

[5]. Booth, G.G.; Kaen, F.R.; Koveos, P.E. (1982) *R/S Analyses of Foreign Exchange Rates under Two International Monetary Regimes*, Journal of Monetary Economics, 10: 407-415

[6]. Cheung, Y.W.; Lai, K.S. (1993) *Do Gold Market Returns Have Long Memory?* The Financial Review, 28: 181-202

[7]. Chow, K.V.; Denning, K.C.; Ferris, S.; Noronha, G. (1995) *Long-Term and Short-Term Price Memory in the Stock Market,* Economic Letters, 49: 287-293

[8]. Doornik, J.A.; Hansen, H. (2008) *An Omnibus Test for Univariate and Multivariate Normality*, Oxford Bulletin of Economics and Statistics, 70: 927-939

[9]. Eisler, Z. (2007) *Fluctuation Phenomena on the stock market*, PhD. Thesis, Budapest University of Technology and Economics, Budapest

[10]. Erfani, A.; Samimi, A.J. (2009) *Long memory forecasting of stock price index using a fractionally differenced Arma model*, Journal of Applied Sciences Research, 5(10): 1721-1731

[11]. Fang, H.K.; Lai, S.; Lai, M. (1994) *Fractal Structure in Currency Futures Price Dynamics*, The Journal of Futures Markets, 14(2): 169-181

[12]. Golinelli, R.; Parigi, G. (2008) *Real-Time Squared: A Real-time Data set for Real-Time GDP Forecasting*, International Journal of Forecasting, 24(3): 368–385

[13]. Granger, C.W.J.; Joyeux, R. (1980) *An Introduction to Long-Memory Time Series Models and Fractal Differencing*, Journal of Time Series Analysis, 1: 15-29

[14]. Helms, B.P.; Kaen, F.R.; Rosenman, R.E. (1984) *Memory in Commodity Futures Contracts,* The Journal of Futures Markets, 10: 559-567

[15]. Hosking, J.R.M. (1981) *Fractal Differencing,* Biometrika, 68: 165-176

[16]. Hurst, H.E. (1951) *Long-term storage capacity of reservoirs*, Trans. Am. Soc. Civil Engrs., 116: 770-808

[17]. Hurst, H.E. (1952) *The Nile,* Constable and Company, England

[18]. Kohzadi, N.; Boyd, M.S.; Kermanshahi, B.; Kaastra, I. (1996) *A comparison of artificial neural network and time series models for forecasting commodity prices*, Neurocomputing, 10(2): 169-181

[19]. Korkmaz, T.; Cevik, E.I.; Özatac, N. (2009) *Testing for Long Memory in ISE Using ARFIMA-FIGARCH Model and Structural Break Test*, International Research Journal of Finance and Economics, 26: 186-191

[20]. Koscielny-Bunde, E.; Bunde, A.; Havlin, S.; Roman, H.E.; Goldreich, Y.; Schellnhuber, H.J. (1998) *Indication of an universal persistence law governing atmospheric variability,* Physical Review Letters, 81: 729-732

[21]. Lilliefors, H. (1967) *On the Kolmogorov–Smirnov test for normality with mean and variance unknown*, Journal of the American Statistical Association, 62: 399–402

[22]. Mandelbrot, B. (1969) *The Robustness of the Rescaled Range R/S in the Measurement of Noncyclic Long-Run Statistical Dependence*, Water Resources Research, 5: 967-988

[23]. Nyárs, L. (2005) *A magyar sertéshústermelés gazdasági környezetének vizsgálata*, PhD-értekezés, Gödöllő, (Working paper)

[24]. Peng, C.K.; Buldyrev, S.V.; Goldberger, A.L.; Havlin, S.; Sciortino, F.; Simons, M.; Stanley, H.E. (1992) *Long-range correlations in nucleotide sequences,* Nature, 356: 168-170

[25]. Peng, C.K.; Buldyrev, S.V. Goldberger, A.L.; Havlin, S.; Simons, M.; Stanley, H.E. (1993) *Finite-size effects on long-range correlations: Implications for analyzing DNA sequences,* Physical Review E, 47: 3730-3733

[26]. Peng, C.K; Buldyrev, S.V.; Havlin, S.; Simons, M.; Stanley, H.E.; Goldberger A.L. (1994) *Mosaic organization of DNA nucleotides*, Physical Review E, 49: 1685-1689

[27]. Peng, C.K.; Havlin, S.; Stanley, H.E.; Goldberger, A.L. (1995) *Quantification of scaling exponents and crossover phenomena in nonstationary heartbeat time series Chaos*, 5: 82-87

[28]. Power, G.J.; Turvey, C.G. (2010) *Long-range dependence in the volatility of commodity futures prices: Wavelet-based evidence*, Physica A: Statistical Mechanics and its Applications 389(1): 79-90

[29]. Ramirez, J.A.; Alvarez, J.; Rodriguez, E. (2008) *Short-term predictability of crude oil markets: A detrended fluctuation analysis approach*, Energy Economics, 30(5): 2645-2656

[30]. Sewell, M. (2010) *Rescaled range analysis software*, http://www.long-memory.com/

[31]. Shahwan, T.; Odening, M. (2007) *Forecasting Agricultural Commodity Prices using Hybrid Neural Networks*, In: Computational Intelligence in Economics and Finance (Eds: Shu-Heng Chen, Paul P. Wang and Tzu-Wen Kuo), Springer, Berlin, 63-74

[32]. Sriboonchitta, S.; Chaitip, P.; Balogh, P.; Kovacs, S.; Chaiboonsri, C. (2011) *On Tests for Long Memory Process Behavior of International Tourism Market: Thailand and India*, APSTRACT: Applied Studies in Agribusiness and Commerce, 2011, 05

[33]. **Talkner, P.; Weber, R.O.** (2000) *Power spectrum and detrended fluctuation analysis: Application to daily temperatures,* Physical Review E, 62: 150-160

[34]. **Taylor, S.** (1986) *Modelling Financial Time Series*, John Wiley & Sons, Inc. New York

[35]. **Telcs, A.** (2009) *Igazságos játékok a pénzfeldobástól a tőzsdéig*, BME, Budapest, 157-158 http://www.szit.bme.hu/~telcs/pfj.pdf

[36]. **Tomek, W.G.** (1994) *Dependence in Commodity Prices: A Comment*, The Journal of Futures Markets, 14: 103-109

[37]. **Tsypalkov, A.** (2004) *Matrixer econometric program*, http://matrixer.narod.ru/

[38]. **Wei, A.; Leuthold, R.M.** (2000) *Agricultural Futures Prices and Long Memory Processes*, Working paper No. 00.04, Social Science Research Network http://papers.ssrn.com/sol3/papers.cfm?abstract_id=229795

[39]. **Ksh stADAT-táblák** (2010) *A fontosabb élő állatok átlagára az állatpiacokon és –vásárokon. Malac, süldő, anyakoca, vágósertés átlagára az állatpiacokon és –vásárokon 2006-tól 2010-ig.* http://portal.ksh.hu/pls/ksh/docs/hun/xstadat/xstadat_evkozi/e_qsma006b.html

[40]. **Magyar Statisztikai Évkönyv** (1991-2006) KSH, Budapest

[41]. **PhysioNet statistical softver** (2010) *Detrended Fluctuation Analysis*, www.physionet.org/physiotools/dfa/