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LAMB PRICE PREDICTIONS IN SOME EU CONTRIES USING TIME SERIES FORECASTING METHODS

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Abstract

Characteristically, European lamb prices largely fluctuate seasonally. Our research in lamb trade inspired us to analyze the predictability of price formation. In total, we set up 10 competing models for the prediction of lamb price. Out of 10 variants seasonal decomposition was the method, which approximated original data most precisely. ARIMA (1,1,0) came to the second, ARIMA (1,1,1) to the third place. The difference between ARIMA (1,1,0) and ARIMA (1,1,1) is that in the ARIMA (1,1,0) model we did not take the MA (q) parameter into consideration. The poorest approximation was produced by the Winter-type exponential smoothing.

Key words: time series, forcasting, lamb prices, comparison

INTRODUCTION

Within the export of sheep products from Hungary, lamb (slaughter lamb) and live animal export are of determining importance. The market for live slaughter sheep was the Near East in the 1960s and 1970s, but this has ceased. Nowadays, the number of animals sold outside of the EU (in Croatia, Bosnia and Switzerland) is only some ten thousands (Nábrádi, 1998). More than 90% of the Hungarian sheep meat export goes to Italy. Accordingly, the market is quite limited with respect to demand and supply, selling weight and level of processing (Jávor et al., 2001). In addition to the sole Italian market with a continuous demand for Hungarian lamb, other solvent European market possibilities meeting the transport regulations should also be seized. Such markets could be the Spanish and Greek ”light” lamb markets with temporary demand and the French, German or Austrian ”heavy” lamb markets. Due to the price fluctuations, the sheep breeders frequently have large losses, therefore, the adaptation of production to seasons and the market research and technological development should all be improved. Simultaneously with opening to new markets, great attention should be paid to keeping the Italian market, since Bulgaria and Romania, which have joined the EU in January 2007, can be strong competitors for Hungary and also for the Hungarian Sheep Sector (Madai, 2007.) One condition of maintaining our market position is to improve quality and uniformity of our products. European lamb prices show great seasonal fluctuation, the degree and time of changes varies among the different countries. Study of the literature and our examination results in lamb trade inspired us to analyse and study the predictability of prices. In our study, we have performed a price forecast for Hungarian lamb for the period of 1998-2006 based on the database of the Sheep Product Council. Our aim was to provide decision support for farmers, so that they would inseminate and produce in harmony with the market requirements, thereby, the present uncertainty of sales would reduce and the profitability of sheep breeding would improve.

MATHERIAL AND METHODS

Statistical methods include specials ones that advance future decision-making. The common characteristic of these predictions is that they are based on so-called time series, i.e. we know the past and present data of the investigated phenomenon, and we seek to draw conclusions for the future from them. Predictions differ according to the rate they take the changes of circumstances into consideration (Balogh – Ertsey, 2003, Balogh, 2003). During the preparation of our study we investigated and compared different time series forcasting methods (Seasonal decomposition, Fourier analysis, Moving average process, Box-Jenkins type time series models /ARIMA/, Winters' exponential smoothing, Seasonal decomposition) in relation to their applicability in lamb price prediction. In the case of seasonal decomposition time series are divided into four varying parts: the factor following seasonal effect, trend and cycle components and error terms. Cycle components are significant if time series are of considerable length.

Given that S_t means seasonal fluctuation at a given t point of time, T_t means the trend component, C_t the cycle component and I_t means random effects, i.e. error terms. The combination of trend and cycle components forms the TC_t component.

Additive model:

$$X_t = TC_t + S_t + I_t \qquad (1)$$

Multiplicative model:

$$X_t = T * C_t * S_t * I_t \qquad (2)$$

Estimation performed by the multiplicative variant of seasonal decomposition proved better than the additive one, therefore we chose this. In the course of additive estimation the square of the difference between original and estimated data far exceeded the one gained by multiplicative estimation. Based on decomposition, the estimation was prepared by taking the seasonal index related to the given time period into consideration. We broke down the trend-cycle effect into trend effect and cycle effect by fitting a trend line on the original data series. Then, dividing trend cycle values by trend values we received the values of cycle components. The values of cycle components in relation to time period n calculated in this way, were multiplied with the seasonal index and trend values relating to period n+1, and thus we received our estimated values for the coming 1 month.

Fourier analysis:

The simple variant of the method is Fourier's method, which identifies periodical structures (cycles) in time series. Assume that we have a given time series in the form of a given f(t) continuous function, where t is the time factor. Our time series only include finite N pieces of xk elements for given tk points of time, where $t_k = k\Delta t$ and k =0, …,N-1. On the basis of N pieces of xk elements of the time series we formed a coefficient of N complex Fn , which was calculated in the following way:

$$F_n = \sum_{k=0}^{N-1} x_k e^{ik\frac{2\pi n}{N}}, \tag{3}$$

where $i = \sqrt{-1}$, and $e^{ix} = \cos(x) + i\sin(x)$ (4)

equation is based on Euler's formula valid for complex numbers.
Then, the discrete Fourier-type formation of the fk elements in our time series is:

$$x_n = \frac{1}{N} \sum_{n=0}^{N-1} F_k e^{-ik\frac{2\pi n}{N}}. \tag{5}$$

The more popular form of the above formula is:

$$x_n = \frac{1}{N} \sum_{n=0}^{N-1} F_k e^{-in\omega_0 t_k} \tag{6}$$

, where ω_0 is the frequency.

The essence of Fourier's transformation is that it maps a continuous function into the frequency space and breaks it down into the compound of sinus and cosinus functions. In fact, Fk coefficients serve as the amplitudes of trigonometrical functions. The EXCEL FFT (Fast Fourier Transformation) function calculates these discrete Fourier coefficients. By this we can analyse the cycles of data series and we can describe them by function approximation, and we can provide further estimations. By the application of Discrete Fourier Analysis we reconstructed the original data series, and then minimized the original and reconstructed difference by a solver and perfected the approximation. Pre-estimation was prepared in two ways: by the further calculation of function values and fitting them to the previous year (Fourier 1) and to the first year (Fourier 2), by shifting. The first estimated value was approximated to the original values by a solver, and then we received the pre-estimation of the following data by altered amplitude and phase. Then the first 2 estimated values were approximated to the original ones by a solver and we received the third pre-estimated value by altered amplitude and phase. This process was repeated until we received 24 estimations.

ARIMA models:

The most sophisticated and complex analysis is available through ARIMA models developed by Box and Jenkins. ARIMA models postulate some kind of inner, stochastic coherence among time series data, which steadily exist, which are demonstrable and likely to be present in the course of future processes. In this way, as a result of careful analysis, exact predictions can be expected in these models. Most of random processes, which occur in practice and show stationary nature, can be well approximated by ARIMA processes.

General ARIMA models can be characterized by the parameters of two orders and one degree as follows: ARIMA (p,s,q). In autoregressive (AR) models the value of t-time point can be taken as the weighted sum of past values (or their linear combination) and as the sum of uncorrelated error terms. In the expression of AR (p) p is the order of autoregression. In moving average models (MA) time series are characterized by of a kind of moving average of an infinite error term process and the sum of an uncorrelated error term. In the expression of MA (q) q is the order of moving average. In integrated (I) ARIMA models we assume time series with ARMA-type derived series. Derived series are data series formed from the difference of neighbouring elements. In the expression of I (s) s is the degree of differentiation. If zero value occurs among p, s and q parameters, we usually speak about AR(p), ARMA (p,q), ARIMA (p,s,q), Ma (q) models (Ketskeméty – Izsó, 2005). On the basis of the time series graphs, autocorrelation graphs (ACF) and partial autocorrelation functions (PACF) we can establish the probability of fitting the appropriate order and degree of successful ARIMA processes. On the grounds of our data we verified the probability of ARIMA (1,0,0) model, but we performed our calculations for further three models: (ARIMA (1,1,0); ARIMA (1,1,1); ARIMA (1,0,1)).

$$(1-\sum_{i=1}^{p}\phi_i X_{i-k})\Delta^d X_t = (1+\sum_{i=1}^{q}\phi_i X_{t-i})\varepsilon_t \qquad (7)$$

$\Delta X_t = X_t - X_{t-1}$, $\Delta^d X_t = \Delta^{d-1} X_t - \Delta^{d-1} X_{t-1}$

Moving average:

Moving average, produced as the dynamic average of original time series, is a practically widely used, simple and fast method, which is occasionally more suitable for the description of basic trends than analytic trend calculation. Its disadvantage is that it shortens the time series, i.e. as a result of averaging, the received balanced time series are shorter than the original ones. Therefore, its use is only advisable in the case of long time series (Ertsey, 2002). This method is one of the most generally used ways of predictions. Assume $x_i, x_2 .... x_t$ as the studied values of our time series, where x_t is the value of time series at t time point. After observing x_t we can define $f_{t,1}$ as the prediction of period t+1 by using formula (8):

$$f_{t,1} = \frac{\sum_{i=t}^{t-N+1} x_i}{N}, \qquad (8)$$

where N is a given parameter. In the moving average method it is significant to select N, the number of periods used in the moving average. For the correct selection of N the index number measuring the preciseness of prediction, average absolute deviation (MAD) is to be defined. The definition of MAD requires the introduction of the notion of prediction error. Given a prediction relating to x_t, e_t is calculated by formula (9):

$$e_t = x_t - (\text{predicted } x_t) \qquad (9)$$

MAD is simply the average of e_t absolute values. It is reasonable to select N to have minimal MAD values (Winston, 2003). In our study, the 2 and 3-member moving averages met these requirements.

WINTER's exponential smoothing :

Information in time series provides opportunities for prognostication, i.e. for the estimation of future expectable values of studied phenomena on the basis of past experience. Smoothing methods are parts of these processes, which continuously correct the model on the grounds of prediction errors, placing higher emphasis on recent information than on earlier ones (Ertsey, 2002). Out of smoothing methods, we used Winter's one, which prognosticated time series applying trends and seasonality as well. We chose this method as seasonal demand in export markets is significant in three periods of Hungarian slaughter lamb trade: Easter, Ferragusto and Christmas. The description of Winter's method requires two definitions. Assume c as the number of periods alongside the seasonal pattern (in the case of monthly data, c= 12). After the observation of x_1, s_t is our estimation referring to the seasonal index of period t, L_t is the estimated basic level of time series and T_t means the trend of the period. The values of L_t T_t and s_t (in this order) are re-calculated for each period by formula (10)-(12):

$$L_t = \alpha \frac{x_t}{S_{t-c}} + (1-\alpha)(L_{t-1} + T_{t-1}) \quad (10)$$

$$T_t = \beta(L_t - L_{t-1}) + (1-\beta)T_{t-1} \quad (11)$$

$$s_t = \gamma \frac{x_t}{L_t} + (1-\gamma)s_{t-c} \quad (12)$$

where α, β, and γ are smoothing constants from 0 to 1(Winston, 2003). The (10) equation updates our estimation referring to the base of the time series as the weighted average of the following two quantities:

1. $L_{t-1} + \mathrm{T}_{t\text{-}1}$, which is our starting point estimation before observing x_1
2. Our observation $\frac{x_t}{S_{t-c}}$ (without seasonality), which is our starting point estimation from the actual period.

Equation (11) is calculated as the weighted average of the following two quantities:
1. Estimation referring to the trend from the given period, i.e. the growth of the smoothed base from period $(t-1)$ to period t.
T_{t-1}, which is our previous estimation referring to the trend
The equation (12) updates the seasonality estimation of month t as the weighted average of the following two quantities:

(s_{t-c}), the latest estimation of the seasonality of period t

$\frac{x_t}{L_t}$, our estimation from the current month for the seasonality of month t.

Our prediction for the end of period t, for month $(t+k)$ is:

$$f_{t,k} = (L_t + kT_t)s_{t+k-c} \quad (13)$$

therefore, to get our prediction for the period of $(t+k)$ we multiply our starting point estimation for the $(t+k)$ period $((L_t + kT_t) - t)$ with the seasonal index (s_{t+k-c}) related to the newest $(t+k)$ period.

RESULTS AND DISCUSSIONS

In total, we set up 10 competing models for the prediction of lamb price. The models are the following:

Seasonal decomposition
ARIMA (1,1,0)
ARIMA (1,1,1)
ARIMA (1,0,0)
ARIMA (1,0,1)
Moving average (3 elements)
Moving average (2 elements)
Winter-type exponential smoothing
Fourier analysis 1
Fourier analysis 2

For the evaluation of the predictability of models we predicted the next month, January of 2005 on the basis of the period in January 1998-December 2004. Then, on the basis of the period in January 1998-January 2005 we predicted February in 2005 and so on until December 2006. The results of our calculations are presented in Figure 1. The question emerged, what aspects render a given prediction better than another one. The question seems to be easy, but the answer is difficult. Therefore we considered the prediction should not deviate from factual data, i.e. we should be able to estimate the future values of the given variable as precisely as possible. In order to ranking the various methods we made the following steps:
We calculated deviations between original and predicted data
Based on the absolute value of deviations, on the grounds of data calculated for the periods we ranked the methods.

Figure 1: Results of predictions on lamb price based on 10 competing models

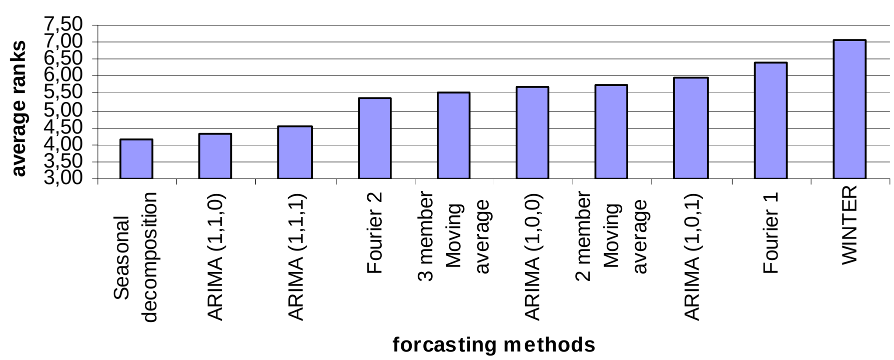
		Szezonális dekompozíció	Fourier 1	Fourier	ARIMA (1,1,0)	ARIMA (1,1,1)	ARIMA (1,0,0)	ARIMA (1,0,1)	mozgó átlag (2 tagú)	mozgó átlag (3 tagú)	WINTER	EREDETI
2005	január	636,12	638,53	627,93	624,66	631,26	634,33	612,91	620,20	587,23	598,26	635,20
	február	610,95	597,53	628,14	614,71	626,15	642,94	618,92	641,65	625,20	557,34	575,20
	március	618,93	600,41	947,70	566,44	588,83	596,64	582,94	605,20	619,50	577,95	662,70
	április	587,08	621,45	666,98	637,08	644,88	638,16	626,79	618,95	624,37	551,53	657,90
	május	630,80	525,71	586,79	633,89	645,32	663,33	637,69	660,30	631,93	533,85	613,50
	június	634,07	601,13	573,08	598,07	619,48	630,87	613,43	635,70	644,70	544,44	606,27
	július	699,89	600,02	644,52	592,47	615,45	611,57	601,70	609,89	625,89	582,47	683,99
	augusztus	669,77	636,08	663,73	656,21	664,80	663,38	646,09	645,13	634,59	596,57	657,41
	szeptember	717,51	637,66	676,08	634,93	651,38	669,61	644,15	670,70	649,22	651,20	669,81
	október	674,89	643,72	652,96	645,82	661,17	669,69	651,53	663,61	670,40	645,89	708,35
	november	698,58	643,19	678,27	679,00	687,93	700,42	678,51	689,08	678,52	668,28	720,05
	december	752,04	652,48	716,12	690,24	699,21	720,80	695,29	714,20	699,40	700,27	770,87
2006	január	760,77	669,34	679,13	736,14	736,61	759,96	734,58	745,46	733,09	712,85	753,91
	február	704,95	626,63	693,31	722,90	731,05	764,10	736,54	762,39	748,28	666,32	655,53
	március	716,67	796,05	786,97	638,01	669,47	689,33	671,73	704,72	726,77	706,14	654,44
	április	698,25	687,22	670,78	637,42	668,31	658,10	651,36	654,99	687,96	673,07	698,25
	május	630,31	828,88	707,95	675,21	697,11	689,05	674,18	676,35	669,41	640,15	665,78
	június	668,86	702,34	691,66	647,82	677,35	678,99	660,53	682,02	672,82	646,80	685,13
	július	679,96	689,61	683,97	664,81	690,11	682,93	668,81	675,46	683,05	698,35	682,23
	augusztus	708,25	686,26	682,82	662,78	689,03	686,68	669,78	683,68	677,71	698,94	759,71
	szeptember	765,20	698,93	704,50	730,92	739,62	740,73	719,77	720,97	709,02	753,18	768,39
	október	788,25	725,87	708,85	739,97	748,73	770,37	742,70	764,05	736,78	757,95	756,97
	november	783,95	747,25	726,13	730,87	744,81	764,75	742,67	762,68	761,69	776,93	689,90
	december	805,53	736,37	733,28	671,96	703,90	713,14	698,19	723,44	738,42	802,55	674,68

Source: own calculations on the basis of the database from the Association of Sheep Products

1.We totalled up these ranks and we could conclude that seasonal decomposition proved to be the method, which came first 8 times out of 24 occasions and came second in total 4 times out of 24 occasions. Fourier's 1 (6 times) and the Winter-type exponential smoothing (8 times) came last most of the time.

2.From the totalled ranks we calculated the average ranks of the methods. The results are presented in Figure 1.

Figure 2: Average ranks of prediction methods



Source: own calculations on the basis of the database from the Association of Sheep Products

Summing up we can conclude that out of 10 variants, seasonal decomposition was the method, which approximated original data most precisely. ARIMA (1,1,0) came to the second, ARIMA (1,1,1) to the third place. The difference between ARIMA (1,1,0) and ARIMA (1,1,1) is that in the ARIMA (1,1,0) model we did not take the MA (q) parameter into consideration. The poorest approximation was produced by the Winter-type exponential smoothing.

CONCLUSIONS

On the basis of the 10 types of prediction models we can state that seasonal decomposition proved to be the most suitable for the prediction of lamb prices, followed by ARIMA (1,1,0) and ARIMA (1,1,1) models. The most unpunctual predictions were given by Fourier's 1. model and by the Winter-type exponential smoothing.

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