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AUTOREGRESSIVE MODELS USED FOR FORECASTING THE PRICES OF ANIMALS FOR SLAUGHTER IN POLAND

Abstract: The forecast of agricultural prices is one of the most important factors in making decision on production farms. The appropriate forecast allows for limiting the risk connected with one's economic activity. In this study autoregressive models have been used, which helped to determine the price forecast for agricultural products in the purchasing centres in the three quarters of 2010. To determine the quality of forecast the average ex-post errors of the past forecasts have been used. The achieved results show that autoregressive models are an effective tool in forecasting the agricultural prices in Poland.

Key words: the prices of animals for slaughter autoregressive models, forecasting.

1. Introduction

In a contemporary, quickly developing world, the ability to forecast the socio-economic phenomena has gained crucial significance. The key capability of contemporary managers is the ability to use the existing tools for the preparation of forecasts. The knowledge connected with the preparation of forecasts becomes more and more desirable in the process of managing. The establishment of forecasts leads to a decrease of uncertainty and causes an increase of the accuracy of the decisions made and, at the same time, eliminates the loss in different areas of economic activity. This information is necessary to make accurate decisions for households breeding the animals destined to slaughter or growing cereal, the plants processing them or the units which deal with the trade of the processed agricultural goods [Majewski 2006].

In literature there are many methods dealing with the forecasts of agricultural prices presented. This work presents the possibility of usage, of the widely presented in literature, autoregressive models for the forecasts of prices of the chosen agricultural produce in a purchasing centre.

2. Autoregressive models and the forecast precision measurements

One of the main tasks of econometric modelling is to define the accuracy of the changes of the level of the examined phenomenon in time. With this end in view dynamic models are used which include the time factor. Such models allow for consideration of the changes taking place in time in the relationship between the variables. In econometric modelling, models with a delayed value of variables are frequently used. This is caused by the fact that very frequently the influence of a variable or explanatory variables on the explained variable is not immediate but appears with a certain delay. The reasons for time delays in economic relations can be divided into three groups: psychological, technological, institutional-legal. The majority of delays present in agriculture are connected with:

– habits of agriculture producers connected with the ways of managing,
– frequently expensive changes in the direction of production,
– commitments resulting from contracts, unabling immediate change in a direction of production [Gruszczyński, Podgórska 2004].

The group of models with the delayed variables includes the autoregressive models which come from a wider category of regressive models used in modelling of economic processes. In these models the current value of the variable is expressed as a finite combination of its past values. These models can be used to model the stationary time sequences or time sequences convertible to stationary. The formula expressing the autoregressive model of a p rank is presented as follows:

$$y_t = \varphi_0 + \varphi_1 y_{t-1} + \varphi_2 y_{t-2} + ... + \varphi_p y_{t-p} + e_t, \tag{1}$$

where: $y_t, y_{t-1}, \ldots, y_{t-p}$ – the value of the changeable variable forecasted in moment or in time $t, t-1, \ldots, t-p$;
ε_t – residual process (white noise),
$\varphi_0, \varphi_1, \ldots, \varphi_{t-p}$ – model parameters,
p – autoregression rank, the maximum delay of the explained variable.

There are four stages of creating autoregressive models for example: verification whether the time sequence is stationary and the establishment of the maximum delay rank, estimation of the parameters of the model, verification, and forecasting.

The first thing to do is to check whether the considered time sequence is stationary.[1] A test which is most frequently used to measure the stationarity is DF test (Dickey–Fuller test) which is also called a unit root test. The tested equation is as follows:

$$y_t = \rho y_{t-1} + \varepsilon_t. \tag{2}$$

[1] Stationarity of a time sequence can be understood as: lack of trend, lack of systematical changes in variance, lack of periodical deviation. In econometric research there are two types of stationarity: stationarity in a wider sense and in a narrow sense. The verification of the stationarity in a narrow sense is very difficult thus it is more useful to verify the stationarity hypothesis in a wider sense. A time sequence is called stationary in a wider sense if the average and variance are finite and constant in time and covariance depends only on a difference of periods between the two observed variables. The question of stationarity of time series in wider and narrow senses is described in the works of J.D. Hamilton [1994, pp. 45–46], Ch. Chatfield [2004, p. 34], M. Gruszczyński and M. Podgórska [2004, pp. 181–183].

The zero hypothesis speaks about the existence of at least one unit root in the examined time sequence, and the alternative one speaks about its lack and is expressed as follows:

$H_0: \rho = 1 \Rightarrow y_t \sim I(1)$,

$H_1: \rho < 1 \Rightarrow y_t \sim I(0)$.[2]

The practical use of the test requires the following changes in equation (2):

$$\Delta y_t = \delta y_{t-1} + \varepsilon_t. \tag{3}$$

Then the responding hypotheses are as follows:

$H_0: \delta = 0 \Rightarrow y_t \sim I(1)$,

$H_1: \delta < 0 \Rightarrow y_t \sim I(0)$.

The (2) equation can include a determined term which takes the figure of the constant of the linear trend and a seasonal term. The appropriate modifications of the equation (2) are:

$$y_t = \alpha + \rho y_{t-1} + \varepsilon_t,\ \ y_t = \alpha_0 + \alpha_1 t + \rho y_{t-1} + \varepsilon_t,\ \text{or}\ \ y_t = \sum_{k=1}^{m} d_k Q_{kt} + \rho y_{t-1} + \varepsilon_t.$$

The Dickey–Fuller statistics checking the presented hypothesis is expressed by the following formula:

$$DF = \frac{\hat{\delta}}{s(\hat{\delta})}, \tag{4}$$

where: $\hat{\delta}$ – the estimation of the parameter form the equation (3) measured by the classic method of the smallest roots,

$s(\hat{\delta})$ – an average estimation error of a δ parameter.

A DF statistics has a non-standard layout left-handedly asymmetrical [Osińska 2006, 2007]. The tables of critical values for DF test were published, among others, in the works of Charemza and Deadman in 1997.[3] The weakness of DF test is the fact that it does not allow for the possibility of autocorrelation of a disturbance term ε_t. The solution suggested by Dickey and Fuller in 1981 is the use of an augmented Dickey–Fuller test (ADF test) [Charemza, Deadman 1997]. The procedure of conducting ADF test is similar to DF test, however, there are different equations tested:

$$\Delta y_t = \delta y_{t-1} + \sum_{i=1}^{k} \alpha_i \Delta y_{t-i} + \varepsilon_t. \tag{5}$$

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[2] Such ways of expressing hypothesis mean consecutively: H_0: an integrated process of a first rank, H_1: process is stationary. Most frequently the values of a lag rank above three suggest that a process is not integrated at all (cf. [Osińska 2007, p. 307; Gruszczyński, Podgórska 2004, p. 187]).

[3] The critical values of a test are different for models with a constant and without it and models with a time variable and without it. The verification of a hypothesis dealing with non-stationarity of series in each of the models requires the use of different tables, however the way of estimation of the statistics and interpretation of a test remain without changes (cf. [Charemza, Deadman 1997, pp. 255–260]).

The hypotheses are presented as follows:

H_0: $\delta = 0 \Rightarrow y_t \sim I(1)$,

H_1: $\delta < 0 \Rightarrow y_t \sim I(0)$.

For the augmented Dickey–Fuller test the same tables of critical values are used as in Dickey–Fuller test.

Another stage is based on the establishment of the autoregression rank and to achieve that the autocorrelations function (ACF) and partial autocorrelations function (PACF) are used.

The ACF function shows the relation between the observations distant in time, where the PACF function show a pre relation between the observations.[4] In practice, to determine the rank of delays the ACF analysis and PACF analysis are completed with a Quenouille's test, in which an autoregressive model is taken into consideration (1).

This test examines the significance of partial autocorrelation coefficient and hypotheses are as follows:

H_0: $\varphi_{pp} = 0$,

H_1: $\varphi_{pp} \neq 0$,

Where φ_{pp} is partial autocorrelation coefficient, that is:

$$\begin{aligned} y_t &= \varphi_{11} y_{t-1} + \varepsilon_{1t}, \\ y_t &= \varphi_{22} y_{t-2} + \varepsilon_{2t}, \\ &\dots \\ y_t &= \varphi_{pp} y_{t-p} + \varepsilon_{pt}. \end{aligned} \tag{6}$$

In Quenouille's test the statistics of the following figure is checked:

$$t = \frac{\hat{\varphi}_{pp}}{s(\hat{\varphi}_{pp})}, \tag{7}$$

where: $\hat{\varphi}_{pp}$ – the estimation of partial autocorrelation coefficient,

$s(\hat{\varphi}_{pp})$ – an average error of estimation of partial autocorrelation factor.

This statistics has a layout of a *t*-Student, if $t \geq 2$ then coefficient is statistically significant. It is accepted that a standard error of partial autocorrelation coefficient is $s(\hat{\varphi}_{pp}) = \frac{1}{\sqrt{n}}$ [Osińska 2007; Hatanaka 2004; Lutkepol, Kratzig 2004].

Next the parameters of an autoregressive model are estimated. This can be done with a classic method of the smallest roots, and the estimators achieved in this way are compatible and asymptotically unbiased. In literature there are also other methods of a parameter estimation presented, for example, with the use of Yule–Walker's set of equations. This method is described in detail in the work of G.E.P. Box and G.M. Jenkins [1983, pp. 63–65]. The estimators achieved from the classic method of

[4] The qualities of ACF and PACF are presented in a more precise manner in the works of: R.S. Tsay [2002, pp. 24–25], H. Lutkepol and M. Kratzig [2004], and Ch. Chatfield [2004].

the smallest roots, in some situations, can be different than those achieved from Yule–Walker's set of equations [Osińska 2006; Tsay 2002].

At this stage of verification the qualities of models' lag are checked, which should have the qualities of a white noise. This means that the lag autocorrelation coefficients should not be significantly different from zero. With this end in view the graphs of ACF and PACF for a lag model series are analyzed. The visual graph analysis of the functions should be completed with a Ljung–Box test in which the statistics is built according to the formula:

$$Q = (n-d)\sum_{k=1}^{K} r_e^2(k), \tag{8}$$

where: $r_e(k)$ – lag autocorrelation function,
n – number of items in an outbound time series,
d – difference operator rank.

Assuming that a given model is suitable the statistics has a layout χ^2 with K-p-q degrees of latitude. The verification of a model should also include the examination of a model's parameters significance. If a model is not positively verified it should return to the first stage and identification should be repeated. A positively verified model is used to prepare a forecast [Zeliaś et al. 2004; Tsay 2002; Dudek 2005; Witkowska et al. 2008].

The accuracy of prediction is connected with the estimation of the accuracy of the forecast based on the basis of the ex-post errors. The quality of prediction is connected with the forecast accuracy based on the ex-post errors. The aim of these measurements is a synthetic description of the empiric arrangement of deviation of the forecasted variable in comparison with the predetermined level of forecast which was achieved in the past in a period of time from which the statistic data was acquired. These measurements provide information about the tendency in forecast errors and thus about possible outdating of models. Among many forecast precision measurements presented in literature the most appropriate seems to be the use of the following measurements: ME – Mean Error, RMSE – Root Mean Squared Error, MAPE – Mean Absolute Percentage Error and I^2 – Theil's index:

$$ME = \frac{1}{m}\sum_{t\in I_p}\left(y_t - y_t^P\right), \tag{9}$$

$$RMSE = \sqrt{\frac{1}{m}\sum_{t\in I_p}\left(y_t - y_t^P\right)^2}, \tag{10}$$

$$MAPE = \frac{1}{m}\sum_{t\in I_p}\left|\frac{y_t - y_t^P}{y_t}\right|\cdot 100, \tag{11}$$

$$I^2 = \frac{mS_p^2}{\sum_{t \in I_p} y_t^2}, \tag{12}$$

where: m – the number of observed pairs,

y_t – actual realizations of the forecasted variable,

y_t^P – the value of the forecast for the forecasted variable,

I_p – the period of empirical verification of the forecast.

These measurements determine the acceptability of forecasts and the size of deviation of the changeable variable realization in comparison with the ready-formed forecast [Zeliaś 1997; Czerwiński, Guzik 1980].

3. Autoregressive models and the forecast of the meat prices

This paper includes the study of configuration of prices of animals for slaughter. The range of research involves the time period from January 1996 to December 2009, which gives a total of 168 observations for every variable analyzed. All data come from the Central Statistical Office Bulletins.

From January 1996 to December 2009 the prices of cattle in a purchasing centre were on the level of 2.4 to 4.9 PLN/kg, reaching the average level of 3.26 PLN/1kg. The consumption of beef during the last few years in Poland has been visibly decreasing in favour of pork and poultry. This situation is the reflection of the increasing prices of this type of meat. However a significant increase of cattle prices was visible during the first year of Polish membership in the EU – during this period the prices increased by 53%. The biggest changes of the cattle prices could be observed in 2001 and 2004. In April 2001 the amount of the purchased beef doubled, however, such a large increase in purchase did not cause significant decreases of prices. In 2004, after the Polish accession to the EU and the opening of the Polish market, Polish meat found consumers abroad and the prices of beef in purchasing centres between April and June 2004 grew by about 40%. The situation on the pork livestock market is strictly connected with the so called "pork cycle",[5] which is present in nature, thus in the pork livestock market there are significant changes of prices and conditions of economy. That is why the price of pork in a purchasing centre is set under the influence of a market mechanism and mostly depends on a demand for pork and its supply on the market. The prices of pig livestock reached a similar level

[5] The pork cycle describes the phenomenon of cyclical fluctuations of supply and prices in livestock markets. Despite many years of research connected with the pork cycle, not one idea has been created, thus, until now there are just opposing theories. One of them looks for the sources of the cycle in external factors and as a direct cause of the fluctuation it takes the instability of the worthwhileness of breeding caused by the changes of pasture and pork prices, bad government policy, etc. The other theory looks for the reason of cyclicality in the very nature of the cycle. Pork cycles count among, so called, special cycles (commodity) having their own mechanism independent of the mechanism of boom changes. The detailed mechanism of pork cycle was presented in the works of S. Stępień [2009, pp. 331–335] and W. Kwaśnicki [2002, pp. 49–64].

to the prices of cattle from 2.5 to 5.1 PLN/kg, and on average they were on the level of 3.72 PLN/kg. Analyzing the changeability factor, which was 15% for pigs it can be stated that the market of pig livestock is relatively stable.

The price series analysis was started from the estimation of their stationarity with an augumented Dickey–Fuller's test (with a vacant expression and a trend).[6] The results of a test for each variable are presented in Table 1. On the basis of ADF statistic data and an adequate probability values (*p*-value)[7] and the level of relevance $\alpha = 0.05$, the zero hypothesis about the existence of a unitary root has been rejected for variable price_of_pigs, whereas for variable price_of_cattle the degree of integration has been established as 2.

Table 1. The results of augmented Dickey–Fuller test for the accepted variables

Variable	ADF statistics value	*p*-value
price_of_pigs	–5.007	.000
price_of_cattle	–3.123	0.098
d_price_of_cattle	–3.277	0.070
dd_price_of cattle	–6.008	0.000

Source: own calculations.

After the stationarity has been checked the next step, in building of autoregressive models, is the establishment of the delays rank. In this case the autocorrelation function ACF and partial autocorrelation function PACF are used. The analysis of diagrams has been supplemented with a Quenouille test. In this test the values of partial autocorrelation function are compared with a critical value.[8]

Figures 1 and 2 present the diagrams of autocorrelation and partial autocorrelation functions for each variable, additionally, the critical values for Quenouille test have been marked.

On the basis of partial autocorrelation function value and a critical statistics value in a Quenouille test the following ranks of delays have been established for each variable: price_of_pigs – 2, price_of_cattle – 7. Taking a degree of integration into consideration together with a line of delay for the analysed variables, the further analysis will include the following models: price_of_pigs – AR(2.0), price_of_cattle – AR(7.2).

The parameters of the model have been estimated using the maximum likelihood method. The model parameters and standard errors are presented in Tables 2 and 3.

[6] The estimations were done in a GRETL program.

[7] During the verification of a hypothesis with the help of computer programs it is important to introduce another ex post level of significance, apart from the already assumed α level of significance. The other level of significance is also called "a computer level of significance" or "a level of probability" and it is marked as *p*-value. If $\alpha > p$-value so on a given level of significance a zero hypothesis is rejected.

[8] The critical value is estimated according to the formula: $\pm 1.96/\sqrt{T}$, where T is a number of observations.

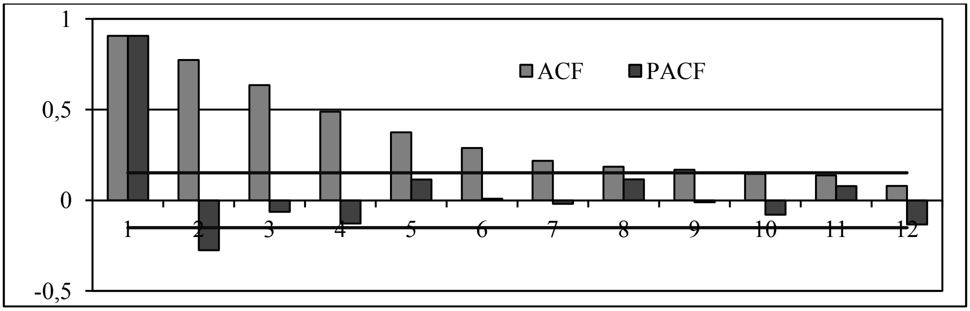

Figure 1. The diagrams of autocorrelation and partial autocorrelation functions for variable price_of_pigs

Source: own calculations.

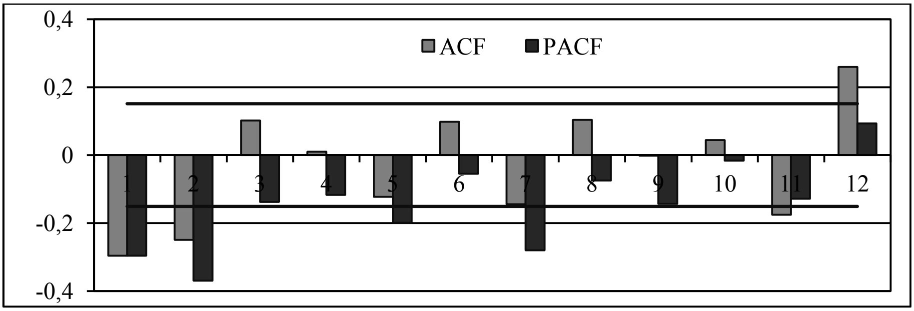

Figure 2. The diagrams of autocorrelation and partial autocorrelation functions for variable price_of_cattle

Source: own calculations.

Table 2. Results of model estimation for variable price_of_pigs

Parameter	Value	Standard error	*t* – statistical value
φ_0	3.685	0.173	21.260
φ_2	1.204	0.074	16.360
φ_1	–0.294	0.074	–3.947

Source: own calculations.

Table 3. Results of model estimation for variable price_of_cattle

Parameter	Value	Standard error	*t* – statistical value
1	2	3	4
φ_0	0.000	0.002	–0.031
φ_1	–0.545	0.074	–7.361
φ_2	–0.627	0.084	–7.439

1	2	3	4
φ_3	–0.405	0.092	–4.439
φ_4	–0.374	0.094	–3.974
φ_5	–0.404	0.092	–4.373
φ_6	–0.206	0.086	–2.393
φ_7	–0.316	0.0787	–4.006

Source: own calculations.

Another stage of the models verification was the examination of the qualities of models' lags, to achieve this, the values of autocorrelation function and partial autocorrelation function of models' lags were analyzed (Figures 3 and 4).[9]

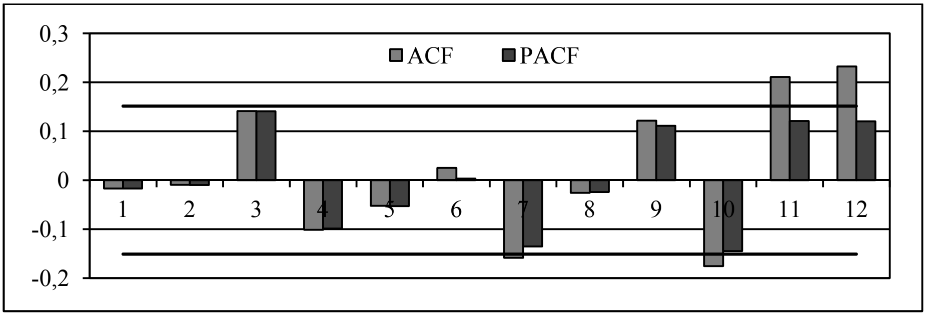

Figure 3. Autocorrelation function and partial autocorrelation function of models' lags diagrams for price_of_pigs

Source: own calculations.

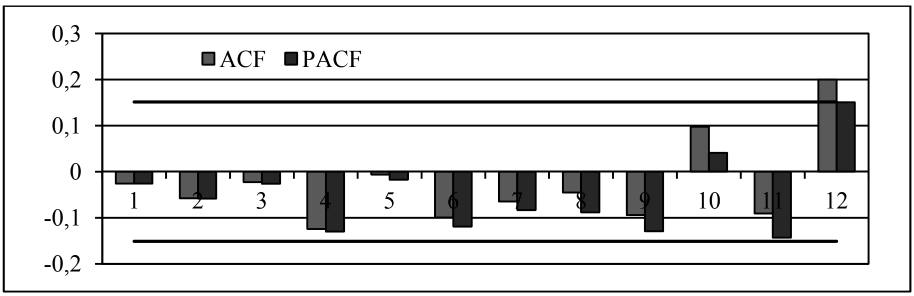

Figure 4. Autocorrelation function and partial autocorrelation function of models' lags diagrams for price_of_cattle

Source: own calculations

[9] In practice, on the diagrams of autocorrelation function and partial autocorrelation function, borders set by double values of standard errors for ACF and PACF functions respectively are marked. For values different than zero only these values are accepted which exceed the marked borders [Dudek 2005].

As a result models were positively verified. Therefore they can be used for forecasting. Figures 5 and 6 present actual values and theoretical values achieved on the basis of the estimated models. The diagrams show a good adjustment of models to the empirical data, which is also confirmed by the values of correlation coefficient between present actual values and theoretical values which respectively equal: 0.921 for a variable price_of_pigs, 0.991 for the variable price_of_cattle, and coefficient of random variation: 5.61% for variable price_of_pigs and 3.20% – price_of_cattle.

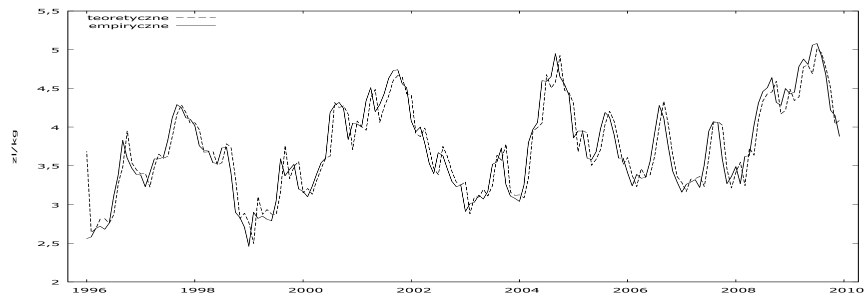

Figure 5. Empirical and equalized, with the help of models, values of variable price_of_pigs

Source: own calculations.

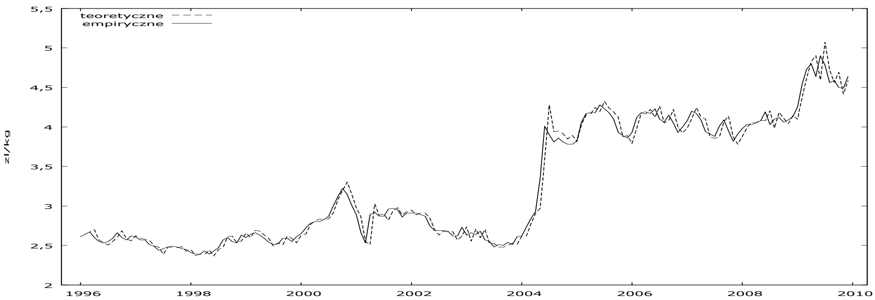

Figure 6. Empirical and equalized, with the help of models, values of variable price_of_cattle

Source: own calculations.

Finally, the models passed the verification phase. They can therefore be used for forecasting purposes. Based on the estimated models forecast prices were determined for the first three quarters of 2010 (table 4).

Table 4. The price animal for slaughter forecasts for the period January–September 2010

Variable	I	II	III	IV	V	VI	VII	VIII	IX
price_of_pigs	3.78	3.75	3.73	3.72	3.71	3.71	3.71	3.70	3.70
price_of_cattle	4.59	4.61	4.64	4.56	4.54	4.54	4.50	4.53	4.54

Source: own calculations.

After the models have been estimated and their quality has been initially checked the evaluation of forecast precision was conducted. With this end in view the ex post measurements of prediction were estimated: ME – Mean Error, RMSE – Root Mean Squared Error, MAPE – Mean Absolute Percentage Error and I^2 – Theil's index. The values of measurements for each model are presented in Table 5.

Table 5. The forecast precision measurements for the estimated models for each variable

Variable	ME	RMSE	MAPE	I^2	I
price_of_pigs	–0.255	0.441	4.89%	0.014	0.118
price_of_cattle	0.027	0.180	3.96%	0.001	0.039

Source: own calculations.

Forecasts designated for the variable price_of_pigs are average, higher than the real value, for the variable price_of_cattle they are lower, which means that the forecasts of pig prices were overestimated (negative value of the parameter ME) and for the price of cattle were underestimated (a positive value of the parameter ME). In the case of variable price_of_cattle these forecasts can be considered accurate, which is shown by the low value of standard deviation of forecast errors, which is 0.180. The forecasts of variable price_of_pigs can be said to be of moderate accuracy – the value of RMSE was 0.441. These values indicate that the forecasted variable price_of_cattle realizations differ from an average by approximately 0.18 zł from calculated forecasts, in the case of variable price_of_pigs these differences are 0.44 zł. While examining the admissibility the forecasts for each variable can be regarded as acceptable. The value of the relative prediction error fluctuates around 4% – for variable price_of_cattle and 5% for the variable price_of_pigs. Their coefficient indicates that the overall relative error of prediction in the empirical verification period is 3.9% for the variable price_of_cattle and 11.8% for the variable price_of_pigs. This suggests that these estimates may be regarded as accurate.

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MODELE AUTOREGRESYJNE W PROGNOZOWANIU CEN ŻYWCA W POLSCE

Streszczenie: Prognozowanie cen produktów rolnych odgrywa dużą rolę we wspomaganiu decyzji produkcyjnych w gospodarstwach rolnych. Poprawne wyznaczenie prognoz cen produktów rolnych pozwala ograniczyć ryzyko związane z prowadzeniem działalności gospodarczej. W opracowaniu autorka przedstawiła możliwość zastosowania modeli autoregresyjnych, za pomocą których wyznaczono prognozy cen podstawowych produktów rolnych w skupie na trzy kwartały 2010 r.

Słowa kluczowe: ceny żywca, modele autoregresyjne, prognozowanie.