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WHEAT MARKET PRICE DYNAMICS IN UKRAINE: QUANTITATIVE EXPLORATION AND FORECASTING

The ARIMA model for forecasting wheat prices in Ukraine was implemented in the investigation. Food prices are vital in economic planning, agricultural management, and food security. Understanding and forecasting food prices helps governments, producers, and consumers make informed decisions about production, consumption, and trade. The instability and unpredictability of food prices have been a serious problem in recent years, which requires developing and applying effective forecasting models. One of the main markets for food products was chosen for the study - the wheat market.

The object of the study is the food market, in particular the wheat market. The subject of the research is wheat price forecasting using the ARIMA model.

The purpose of the work is to research the food market, as well as the development and application of the ARIMA autoregression model for forecasting wheat prices for the domestic market (using Ukrainian data on the dynamics of wheat prices).

The significance of the research work lies in the research of the food market and prices in this market, and in particular, the prices for wheat grain are important for agricultural enterprises, exporters of these products, investors and other market participants. Forecasting the prices of food products makes it possible to make informed decisions about production, purchase, sale of products, as well as to reduce various risks and ensure stability in the food market, and ensure the country's food security.

The method of autoregression modeling, namely the ARIMA model, was used in the study. It is a time series model used to predict the future values of a time series based on its past values. ARIMA models are among the most popular forecasting models because they can model a wide range of time series behavior well. An ARIMA model of the wheat grain price level was built based on Ukrainian data, which explains 67% of the price variation. All model parameters of the model are statistically significant. Improvement of the characteristics of the quality of modeling can be achieved by including in the model other factors that affect the price of wheat.

Keywords: wheat, agriculture, commodity, price, ARIMA, autoregression, time series, dynamics, forecast, model.

Introduction

The grain sector of Ukraine is a strategic branch of the country's economy, which determines the supply and cost of the main types of food for the population, particularly grain processing and animal husbandry products. The grain industry is the source of sustainable development of most branches of agriculture and the basis of the country's agricultural exports. The loss of Ukrainian agrarian production due to the war is of global significance, as Ukraine is a major exporter of grains and oilseeds – mainly corn and wheat, as well as barley, sunflower, and sunflower oil, among other commodities.

Forecasting the wheat price in Ukraine is appropriate for several reasons.

First, wheat is one of the main agricultural crops in Ukraine, and it is an important source of income for Ukrainian farmers. Therefore, wheat price forecasting can help farmers make more informed decisions about wheat production, storage, and sales.

Secondly, Ukraine is one of the largest exporters of wheat in the world. Consequently, wheat price forecasting can help Ukrainian exporters make more informed decisions about pricing and marketing of their products.

Third, the price of wheat is an important factor for other sectors of the economy, such as the food industry, livestock and poultry.

Therefore, forecasting the price of wheat can help these industries make more informed decisions about the production, purchase and sale of their products. Here are some specific examples of how wheat price forecasting can be used in Ukraine:

• Farmers can use wheat price forecasts to plan their planting calendar. For example, if the price of wheat is predicted to be high, farmers may increase the amount of crops.

• Wheat exporters can use wheat price forecasts to determine the best time to sell their products. For example, if the price of wheat is forecast to rise, exporters may wait to sell their products to get a higher price.

• Food businesses can use wheat price forecasts to plan their production. For example, if the price of wheat is predicted to rise, food companies may increase wheat stocks or consider using alternative ingredients.

Of course, wheat price forecasts are not 100% accurate. However, they can help Ukrainian manufacturers, exporters and other stakeholders make more informed decisions.

Literature review

The work of various economists in different countries is devoted to the issue of price forecasting for various types of food products.

In the paper by Wang L and coauthors[1] we can find a review of the methods used for forecasting of the agricultural products prices. Wang Y and coauthors[2] conclude that technical indicators are more effective than economic variables in predicting future changes in commodity prices. Liu L. and coauthors[3] proved the exchange rate of four currencies (AUD, CAD, NZD, and ZAR) can be significantly predicted by movements in commodity prices.

Scientists use different methods for forecasting agricultural commodity prices. For example, Zhang Y., and Wang Y.[4] used principal component analysis for oil futures prices forecasting. Bhardwaj S. and coauthors[5] used autoregressive econometric methods, the same did Zomchak L. and Stelmakh A.[6] Zomchak L., and Umrysh H.[7] used modified ARIMA with seasonal component for meat and eggs forecasting, Degiannakis S. with coauthors[8] used heterogeneous autoregressive model. ARMA model for potato prices

[1] Wang, L., Feng, J., Sui, X., Chu, X., Mu, W. (2020). Agricultural product price forecasting methods: research advances and trend. *British Food Journal*, *122 (7)*, 2121-2138.
[2] Wang, Y., Liu, L., Wu, C. (2020). Forecasting commodity prices out-of-sample: Can technical indicators help?. *International Journal of Forecasting*, *36 (2)*, 666-683.
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[8] Degiannakis, S., Filis, G., Klein, T., Walther, T. (2022). Forecasting realized volatility of agricultural commodities. *International Journal of Forecasting*, *38 (1)*, 74-96.

in Ukraine was used by Koblianska I. and coautjhors[1]. Another group of popular forecasting methods is based on machine learning approach. For example, Zhang D.[2] and coauthors used support vector machine and artificial neural network and extreme learning machine, compared the results and concluded that results depend on different factors. Wang J. and Li X.[3] used neural network models but previously decomposed time series with singular spectrum analysis. Anggraeni W. and coauthors[4] also used artificial neural network for chili price forecasting. Another authors, who used artificial neural network, but for corn price forecasting are Xu X. and Zhang Y.[5] Chen Z. and coauthors[6] used five machine learning methods namely ARIMA, Prophet, SVR, XGBoost and LSTM and concluded that for agricultural commodity prices LSTM was the best one. Paul R. K. and Garai S.[7] used modification of artificial neural network based on wavelet approach. Viedienieiev V. A. and Piskunova O. V.[8] also used artificial neural network for Ukrainian agricultural products. Another modification of machine learning methods - extreme learning machines with seasonal-trend decomposition (termed STL-ELM) was proposed by Xiong T., Li C., Bao Y.[9] Among other methods we will highlight fuzzy logic (papers by Zhang Y. and Na S.[10] and Kozlovskyi S. with coauthors[11]), genetic algorithms (Drachal K. and Pawłowski M.[12] [20]), game theory (Vdovyn M. and coauthors[13]), artificial bee colonies (Wang J. and coauthors[14]), singular spectrum analysis (Chala T. and coauthors[15]), ensemble methods (Ribeiro M. and coauthors[16]) and other.

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[1] Zhang, D., Chen, S., Liwen, L., Xia, Q. (2020). Forecasting agricultural commodity prices using model selection framework with time series features and forecast horizons. *IEEE access*, *8*, 28197-28209.

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ARIMA-model method

The ARIMA model has advantages over other time series forecasting methods because it accepts all data models. ARIMA models are used to forecast past data for short periods that have rapid changes and/or that have qualitative parameters. Forecasting is done by looking at past data to estimate future events, which supports their decision-making and tactical operations activities. Traditional models for time series forecasting, such as the Box–Jenkins model or the autoregressive integrated moving average (ARIMA) model, assume that linear processes generate time series data. However, these models may not be appropriate if the underlying mechanism is nonlinear. Real-world systems are often nonlinear.

The Autoregressive Integrated Moving Average (ARIMA) model is a combination of the autoregressive model taking into account the difference with the moving average model:

• “AR” stands for autoregression, indicating that the model uses a dependent relationship between current data and its past values;

• "I" stands for integrated, which means the data is stationary. Stationary data refers to time series data that have become "stationary" by subtracting observations from previous values;

• "MA" stands for moving average model, indicating that the prediction or output of the model depends linearly on past values. Furthermore, it means that forecast errors are linear functions of past errors.

• The central part of the ARIMA model is the combination of autoregressive (AR) and moving average (MA) polynomials into a complex polynomial. The ARIMA model is applied to all data points for each cost object (labor and materials).

$$y_t = \mu + \sum_{i=1}^{p} (\sigma y_{t-1}) + \sum_{i=1}^{q} (\theta_i \epsilon_{t-1}) + \epsilon_t$$

where y_t – actual data over time;

μ - average value of time series data;

p - number of autoregression lags;

d - the number of differences calculated by equation $\Delta y_t = y_t - y_{t-1}$;

q - the number of cut-off lags of the moving average process;

σ - autoregression coefficients (AR);

θ - moving average coefficients (MA);

t – time, i=1,k;

ϵ - white noise of time series data.

Autoregression modeling of wheat price dynamics in Ukraine

The data of the State Statistics Service of Ukraine on the average monthly prices of wheat sales by agricultural enterprises in the period from January 2014 to December 2021 in hryvnias per ton were used to conduct the research. The data are taken from the statistical collection "Sales of agricultural products by enterprises and households"[1], which was updated monthly. Graphically, the dynamics of price changes per ton of wheat grain are shown in Fig. 1. It can be seen that wheat prices fluctuate depending on the period of the year, so from the beginning of the year prices rise, and at the end of spring, at the beginning of summer they fall and start to rise again by the end of the year. There is also an upward trend in price.

[1] Держстат України (2023). *Головна сторінка* <https://www.ukrstat.gov.ua/> (2023, August, 10).

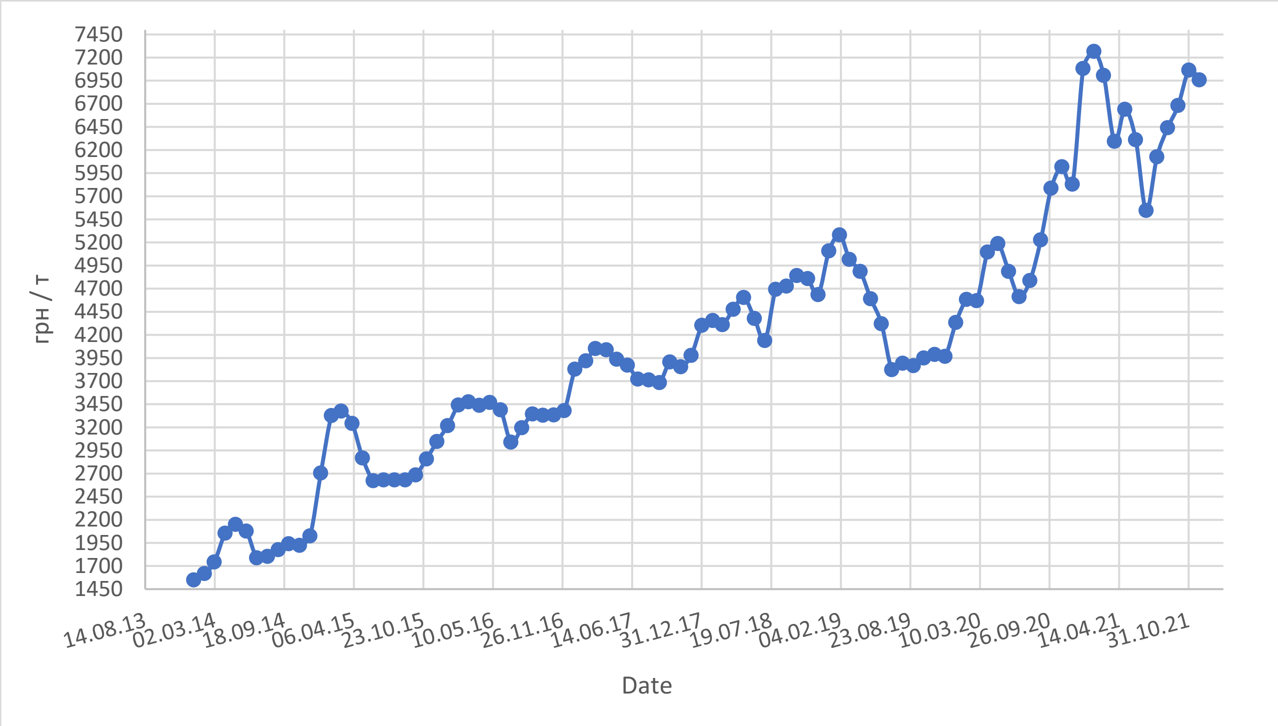

Fig. 1 Dynamics of wheat sales price during 2014-2021

Source: built by the author based on[1]

The first step is to test the time series for stationarity. The extended Dickey-Fuller test is mainly used for this purpose. The essence of this test is to test the null hypothesis about the existence of a unit root. If the null hypothesis is accepted, then the time series is non-stationary. If the hypothesis is not fulfilled, the hypothesis of the absence of a unit root is accepted, then the time series is stationary. We test the original time series. As we can see from the test results, which are shown in Table 1, the value of the t-statistic is greater than the absolute critical values; in addition, the p-value of the test is 0.82, i.e., 82% (p-value > 10%), so we cannot reject the hypothesis regarding the presence of a unit root in the time series, which indicates that the series is non-stationary.

Table 1

The Dickey-Fuller test of testing the wheat price time series in levels for stationarity

Calculated value	-0.7676
Critical value (1%)	-3.5006
Critical value (5%)	-2.8922
Critical value (10%)	-2.5831
Prob	0.8233

Source: calculated by authors

Now we need to check whether it is possible to turn the series into stationary by operating first differences. The test results for the series in the first differences indicate the stationarity of the transformed series. The results of the performed test are shown in Table 2. As you can see, the t-statistic value is smaller

[1] Держстат України (2023). *Головна сторінка* <https://www.ukrstat.gov.ua/> (2023, August, 10).

than the absolute values of the critical value. In addition, the p-value of the test is equal to 0.000, that is, 0% (p-value < 10%). This means rejecting the null hypothesis that there is a unit root in a series of first differences with minimal error (almost 0% out of 100% of cases).

Table 2

The Dickey-Fuller test of testing the wheat price time series in levels for stationarity

Calculated value	-8,1906
Critical value (1%)	-3.5014
Critical value (5%)	-2.8925
Critical value (10%)	-2.5833
Prob	0.0000

Source: calculated by authors

Next, to check the quality of the model specification, the Akaike test of the criterion and the coefficient of determination was performed. Consistent evaluation of AR-components showed that the value of the Akaike criterion is reached at a value of 13.99, while the coefficient of determination is 0.38. Consistent evaluation was achieved for the specification in the following general form:

$$D(price) = m + a_6 D\big(price(-6)\big) + a_{12} D\big(price(-12)\big) + \\ + a_{14} D\big(price(-14)\big) + a_{17} D\big(price(-17)\big)$$

Or in a more standard form:

$$X_t = m + a_6 X_{t-6} + a_{12} X_{t-12} + a_{14} X_{t-14} + a_{17} X_{t-17}$$

where $X_t = D(price)_t$ – the first differences in the price of wheat in the t-time period.

The result of the built AR model is presented in Table 3. That is, among all the built models, the following model with lags 6, 12, 14 and 17 was chosen.

Table 3

The result of the built AR model

Variable	Coefficients	Probability
PRICE(-6)	-0.267302	0.0134
PRICE(-12)	0.356692	0.0079
PRICE(-14)	-0.286175	0.0341
PRICE(-17)	-0.226618	0.0795

Source: calculated by authors

After determining the AR component, it is necessary to form a series of residuals of this model for further use in determining the order of the MA component of the model. When selecting, the model with the smallest value of the Schwartz criterion will be considered the appropriate model. The minimum value is 14.27, while the coefficient of determination is 0.68 and is achieved for the following general model specification:

$$d(price) = m + a_6(price(-6)) + a_{12}(price(-12)) + a_{14}(price(-14)) + \\ + a_{17}(price(-17)) + resid\_price(-11) + resids\_price(-12) + \\ + resids\_price(-17)$$

The results of including a number of residues in the model are presented in Table 4.

Table 4

The result of the constructed ARIMA model

Variable	Coefficients	Probability
PRICE(-6)	-0.179304	0.0982
PRICE(-12)	1.523307	0.0000
PRICE(-14)	-0.201979	0.0979
PRICE(-17)	0.532922	0.0738
RESIDS_ PRICE(-11)	-0.254214	0.0704
RESIDS_ PRICE(-12)	-1.295519	0.0005
RESIDS_ PRICE(-17)	-0.792192	0.0109

Source: calculated by authors

Let's move on to the final evaluation of the model and check its adequacy. For the model to be considered adequate, it is enough that one condition is fulfilled - the residuals of the estimated final equation must be white noise. Correlogram and the Dickey-Fuller test were used to test the residuals for white noise. The residuals are stationary, so we can say that the residuals of the estimated model are white noise and, accordingly, the model can be considered adequate. From the obtained results, it can be seen that the coefficient of determination of the constructed model is 0.68, which means that the price of wheat at the present moment is explained by only 68% of the values in previous periods, and the rest of the sample is explained by other factors. Such factors include demand and supply for wheat, i.e., the predominance of demand over supply leads to the fact that the price may increase and vice versa. Weather conditions, exchange rates, technological changes, seasonality, and others can also be factors influencing the price level. These factors and factors, as well as many others, can interact with each other and influence the formation of the price of wheat in specific conditions. The next step was to build a forecast for the price of wheat. The forecasting results are presented in Fig. 2.

As can be seen from the constructed forecast, the value of the price fluctuates. That is, at the beginning of the year, prices will increase; after that, in the middle of the year, prices will decrease, and by the end of the year, they will increase again. It is possible to explain the decrease in the price in the middle of the year by such factors as, for example, the fact that in the middle of the year, grain crops are often harvested and enter the market, which in turn increases the supply of grain and thereby causes a decrease in prices. Early in the year, the increase in grain prices can be explained by one of the factors in many regions the wheat planting season begins either in late winter or early spring, which means that the demand for grain increases and, accordingly, the price increases.

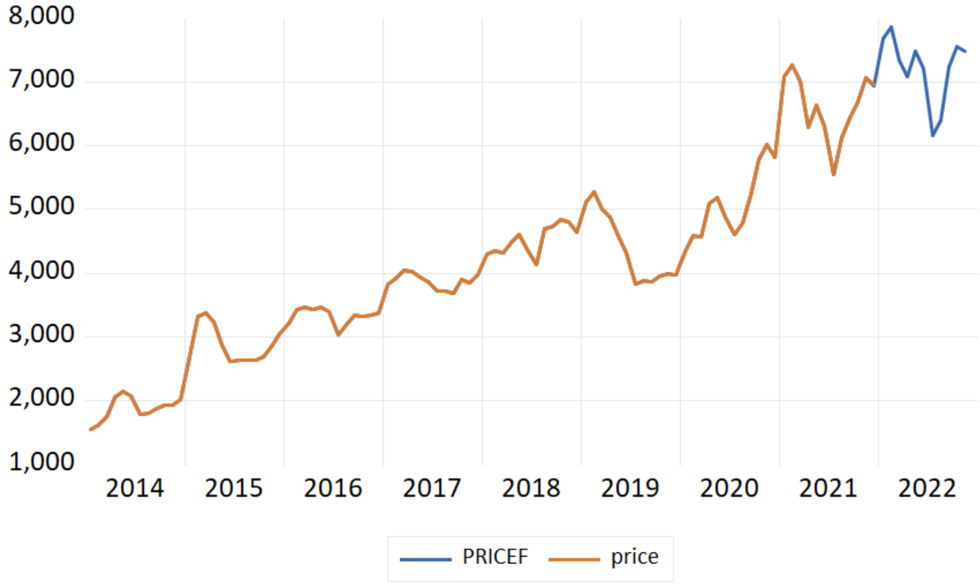

Fig.2 Wheat price forecast based on the ARIMA model

Source: constructed by the authors

Conclusions

The ARIMA model was built for the price level of wheat grain based on Ukrainian data. ARIMA model based on Ukrainian prices explains 67% of price variation. Forecasts of prices for wheat grain for the following periods were obtained on the basis of the developed models. Based on this, it can be argued that the level of wheat grain prices depends not only on the price level in previous periods, but also depends on other additional factors that were not included in the model. Such factors include changes in demand and supply for wheat, changes in weather conditions, which can significantly affect the production of crops and their prices. Also, there are various economic and political factors, such as inflation, exchange rate, various financial crises and political instability. International factors also have an impact on the price level. Such factors can be price changes on world commodity exchanges, various trade agreements and changes in foreign relations. Including these factors in the model can help explain much of the variation in product prices. Therefore, the conducted research of the food market, in particular the grain market, and the built ARIMA model based on Ukrainian data help to understand the dynamics of wheat grain prices and develop forecasts. Taking into account additional factors and improving models can contribute to more accurate price forecasting and understanding of the impact of various factors on the grain market.

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