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Forecasting the prices of agricultural products in Iran with ARIMA and ARCH models

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ABSTRACT

One of the most widely used prediction time series models is Autoregressive Moving Average (ARIMA) model in recent years. In this study; we predict the prices of some agricultural products, including potato, onion, tomato and veal by the first week of data in 2007 to 2015 based on ARIMA model and the results were compared by Autoregressive Conditional Heteroskedactisity (ARCH) model. The results showed that the given estimated due to ARIMA method has less relative error than the estimated through the ARCH model.

1. Introduction

Forecasting of economic variables for each firm is the most important tool in the planning process. Investors, entrepreneurs, and policy makers need to analyze the current and future situations of economic and provide their sales and production decisions based on this information. In competitive markets which a firm has not important role in determining the market price; predicting the future price of the product and production inputs has great importance in the planning of production and sale.

Especially in the agricultural sector in the economy; the uncertainty of future income for farmers increases the risk of activity, mainly due to price fluctuations resulting from production changes or different policies by governments. Forecasting of prices for agricultural products can make farmers improve production and increase real incomes. The agricultural sector policy makers can increase the efficiency of applied policies by forecasting future price, particularly in relation to the products witch support by governments. There are a lot of methods used to predict the time-series variables that mostly revolves around the linear and nonlinear models based on the results of the studies. The aim of this study is to predict the weekly price of agricultural products including onion, potato, tomato and veal.

2. Research background

Most studies examine the relationship between economic time series forecasting to compare different methods of linear and non-linear and its results. In this section, some of the studies will be reviewed in relation to forecasting the economic variables.

Rahmatabadi et al. (2011) have forecast oil prices by evaluating the performance of neural network models and autoregressive moving average. The data used in this study on a weekly basis and covers the period 1977 to 2010. About four different patterns of neural network and autoregressive moving average is used in this study. The results showed an improvement in the results of the survey by using neural networks.

Fahimifard et al. (2008) examined the prices of some agricultural products using neural network - autoregressive with exogenous inputs (NNARX). In this study there are three time periods and its effectiveness with the ARIMA model used to compare the prediction in future retail prices of rice, meat, poultry and eggs. The results of the study indicate that non-linear neural network autoregressive model (NNARX) in prediction is more efficient than linear ARIMA model. The monthly data used for the period 2008 to 2012.

Pourkazemi et al. (2010) have predicted the prices of crude oil using artificial neural network (ANN) model. They forecast by the ARIMA and ANN method and the results were compared with each other. The results of the study showed fewer errors in the artificial neural network model and show that crude oil price forecast error is significantly reduced by adding the storage of OECD countries as input variables to the model.

Abbasi et al. (2014), in a study entitled "Anticipating the liquidity requirements for Automatic Teller Machine (ATM) estimated their model using ARIMA linear and non-linear neural network models. According to study the cash

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withdraw from selected machines using artificial neural networks and ARIMA models during the period 2007 to 2010 for 40 months showed the superiority of the artificial neural network in prediction.

Sabaghyan and Sharifi (2009), in a study predicted their forecast model by creating 50-year time series for annual average rate of a hypothetical river and using ARIMA time series models. Among the various models, the ARIMA (2, 0, 0) or AR (2) is considered as the most efficient model.

Jha and Sinha (2013), in their study entitled "prediction the prices of agricultural products by using artificial neural networks" have studied the price of soybeans and rapeseed, based on monthly wholesale prices of these products by using Time Series and neural networks methods. Studies show better results using artificial neural network for the price of products. In addition, the combination of time series and neural network models is shown more accurate results than using one method alone.

Cristina et al. (2012) in their study have used ARIMA models to determine the usefulness of time series model in analysis of agricultural products prices. The results of the monthly survey data in August 1994 until December 2008 plus the first and last ten months of 2009 Includes the January and December, indicating the desirability of ARIMA time series model to analyze trends and price of these products. ARIMA (2, 0, 0), ALIMA (3, 0, 1), ARIMA (1, 1, 1) and ARIMA (2, 0, 0) processes has been for selected crops such as; peanuts, sugar cane, bananas and oranges in Brazil.

Li et al. (2010), in a study have predicted short-term price of agricultural products using artificial neural network model. And the results of the study were compared with the results of the ARIMA model. Weekly and monthly prices used in the model were based on the price of wholesale goods which is collected during the period from 1996 to 2010 and used in the study. The results show that artificial neural network has relative superiority compare with linear models and the results of this model have less effective relative error.

Alexandridis and Livanis (2008), in their study used wavelet neural network to predict the price of crude oil. In this study, the West Texas Intermediate (WTI) crude oil price data have been used. According to the predictions made in three stages (one-month, three-month and six-month stages) observed that using wavelet neural network based on the real prices predicts near-reality. Period from January 1997 till October 2007 and on a monthly basis has been done for 30 months. In this method the noise in the relevant time series data has been omitted by wavelet transform and the forecast represent the lowest error compare with actual figures.

Ashish and Rashmi (2011), in their study predicts daily air pollution using wavelet analysis and fuzzy network. The air pollution is calculated by calculating the amount of carbon monoxide (CO) in the air for 2007 through Dabshiz wavelet. The results compared with the actual amount represent the effect of addition in wavelet decomposition model to fuzzy methods for improving the results. In this study, 346 data as training data (95 percent) and 19 data as well as test data (5%) have been selected.

Moghadasi and Rajabi (2013), in a study to predict the performance of the global price of wheat, maize and sugar cane, attempt to use different models and compiling them and recommended that to improve the performance of forecasts, it is necessary use compilation of models for this purpose. The study period for selected goods was from the first April 2008 until the second of March 2012, which is used daily. In this study, a combination of ARIMA, GARCH, EGARCH time series models and artificial neural network has used and the results were compared with each other. Survey results indicate that compilation patterns will improve anticipated results significantly.

Homayun et al. (2011), in their study has examined different forecasting models to predict stock market index in Iran. In the study ARIMA, ARCH and GARCH models have been used to forecast major market indicators such as dividend index, price index and the main sub-markets index. The results show that ARCH model offers better results in order to anticipate primary market index and total price index while ARMA model provides better results on the secondary market series price. GARCH model has increased the prediction accuracy in all models.

3. Theoretical fundamental and research method

Forecasting divided into non-regression and regression based on mathematical and statistical methods. Regression methods are in the study also divided into causal and non-causal regression which causal regression method can be autoregressive model with conditional Heteroskedactisity such as ARCH and non-causal regression can be ARIMA models.

3.1. Autoregressive (AR) process

In the autoregressive model, the current value of the variable depends on its previous values plus the error. P-order autoregressive model that displayed by AR (P) can be defined as the following equation (Eq. 1):

$$(Y_t - \delta) = \alpha_1 (Y_{t-1} - \delta) + \alpha_2 (Y_{t-2} - \delta) + \ldots + \alpha_p (Y_{t-p} - \delta) + U_t \quad (1)$$

One of the main characteristics of this process is its stationary, i.e. the previous error factors are decreasing and their impact on (Y_t) gradually reduced. White noise with zero mean and variance of (δ^2) and coefficients (α) are as parameters of the model.

As long as the process is stationary and ($|\alpha_1| < 1$); the ACF function decreasing exponentially. If ($0 < \alpha_1 < 1$), the autocorrelation coefficients are positive and decreasing, and if ($-1 < \alpha_1 < 1$), the autocorrelation coefficients have positive and negative sign alternatively, but its value (its absolute value) would be reduced.

PAC partial autocorrelation function after a break (p) will be zero and this is an important feature for detection of AR in time series patterns. Overall, the partial autocorrelation (PAC) function represents the correlation between current and past observations, so that the effects of field observations have been deleted. In other words, the correlation between Y_t and Y_{t-k} is calculated while the effects of Y_{t-1}, $Y_{t-(k-2)}$,..., $Y_{t-(k-1)}$ is omitted. For example, if the partial autocorrelation function is considered with three breaks, the correlation between Y_t and Y_{t-3} will calculate, while the effects of Y_{t-1} and Y_{t-2} is removed.

3.2. The moving average (MA) process

Moving Average (MA) process is the simplest type of time series model which has normal distribution, zero mean and (δ^2) variance that is defined as the following equation (Eq. 2):

$$Y_t = \mu + \beta_0 U_t + \beta_1 U_{t-1} + \beta_2 U_{t-2} + \ldots + \beta_q U_{t-q} \quad (2)$$

The above equation indicates the process (q) and it is shown as MA (q), briefly. A moving average (q) process can be predicted for (q) periods used to the future based on past trends. Due to reversible condition can find that as long as the MA (q) is invertible, it can be written as AR (∞). Also when a direct correlation between the current value of Y and all of its previous value in the process of moving average, the partial autocorrelation function for the MA (q) model decreasing and will not be zero suddenly. Finally, it can be noted that the (AC) function for the autoregressive (AR) process has the same shape with the (PAC) function for the moving average process and the autocorrelation function for the (MA) process is the same as the partial autocorrelation function (PAC) in the (AR) process.

3.3. The ARMA process

In some cases, the modeling of time series, the very high degree of autoregressive or moving average is required and it is necessary to use the hybrid model autoregressive moving average (ARMA). MA (q) and ARMA (p, q) models is obtained by combining AR (p) process. In this model, the current value of Y depends on its previous values and a combination of current and past values of the error (Eq. 3).

$$Y_t = \mu + U_1 Y_{t-1} + U_2 Y_{t-2} + \ldots + U_p Y_{t-p} + U_t - \theta_1 U_{t-1} - \theta_2 U_{t-2} - \ldots - \theta_q U_{t-q} \quad (3)$$

The feature of this model is a combination of autoregressive and moving average models feature. If the homogeneous part of difference equation has the (p) interruption and the number of interruptions in moving average model is equal to (q); then, the process will be ARMA (p, q). If q = 0, then the ARMA process can be interpreted to pure autoregressive and it is shown as AR (p). If p = 0, then process is pure moving average and it is shown as MA (q).

3.4. ARCH model

In general, it is assumed that the variance of disruption component is constant during the period under study, but large fluctuations can be seen in some courses related to a lot of time series, specially economic and financial series while there is a little change in some periods. In ARCH models the autocorrelation in variation is explained by conditional variance in error stating, therefore an ARCH (1) model is defined as follows:

$$\boldsymbol{P_t = \beta_0 + \sum_{i=1}^{s} \beta_i P_{t-i} + \gamma' X_t + \varepsilon_t}$$

$$\boldsymbol{\varepsilon_t^2 = \alpha_{0+} \sum_{j=1}^{q} \alpha_j \varepsilon_{t-j}^2 + \lambda z_t + v_t}$$

4. Results and discussion

According to the Central Bank of Iran the data included weekly log of consumer prices, for 2007 to 2015 and equal to 444 data of agricultural products, such as; potato, onion, tomato and veal which were analyzed and forecasted by causal and non-causal linear regression methods. Table 1 shows the results. Given that the data is as time series; at the first step the static behavior of series is measured by unit root test and it showed that all data was not static and after one differencing it has been stationary.

Table 1: Dickey-Fuller test with a difference-making

Product	Dickey-Fuller test with a difference-making (ADF)	statistics		
		at 1% level	at 5% level	at 10% level
Potato	-17.322	-3.444	-2.867	-2.570
Onion	-16.856	-3.441	-2.863	-2.570
Tomato	-17.866	-3.456	-32.866	-2.568
Veal	-19.633	-3.444	-2.867	-2.570

In the next step, after data stagnation the break choosing was conducted by Akaic Information Criterion (AIC) and Schwartz Information Criterion (SIC) with multiple breaks test. Table 2 shows the results. In this regard, the criterion of root-mean-square error (RMSE) prediction has been used in order to choosing the rank of AR model through investigating the partial correlation functions. Also the criteria were investigated for other models such as MA and ARIMA which led to the best selection models as the following table.

Table 2: The error coefficient of forecast in selected models

Product	Selected models	RMSE	TIC	MAPE
Potato	AR(2)	0.0504	0.0027	0.3345
Onion	AR(3)	0.0586	0.0032	0.3727
Tomato	AR(2)	0.1262	0.0067	0.813
Veal	AR(3)	0.0291	0.0012	0.0941

4.1. ARCH Model

At the first step the effect of ARCH model should be tested in order to use the ARCH method. In other words; this method cannot be used when the examined series doesn't have the effects of Heteroskedactisity. Therefor the ARCH test is done for variables and results in Table 3 indicate that potatoes and tomatoes don't have the effects of Heteroskedactisity and onions and veal has had such effects. The results in the ARCH model showed the relative superiority of ARIMA method because the prediction error is higher than previous model.

Table 3: The error coefficient of forecast in models ARCH

Product	Selected models	RMSE	TIC	MAPE
Onion	GARCH(1,1)	0.0644	0.0123	0.3911
Veal	GARCH(1,1)	0.0455	0.0111	0.1211

5. Conclusions and recommendations

Among the tested models the prediction accurately of ARIMA model is higher than ARCH model which is confirmed by the less errors observed in series of ARIMA model estimation. Based on the findings from this study we can propose that ARIMA models are better than ARCH models in predictions of selected products in the weekly period.

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