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PREDICTING AND ANALYZING OF TURKISH SUGAR PRICE WITH ARCH, GARCH, EGARCH AND ARIMA METHODS

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Abstract

Using GARCH(p,q) models, in this study our aim is to examine and search the characteristics of volatility of Turkish sugar price. Due to the ARCH effects on price, ARCH(q), GARCH(p,q) and EGARCH(p,q) including these effects on mean and variance equations were estimated. Normal, t-Student, and generalized error distributions with Maximum Likelihood Estimation Method were estimated for these models. Determining the optimal parameters, Marquardt's algorithm (1963) was used for maximizing the log-likelihood function. Mean absolute percentage error (MAPE), root mean square error (RMSE) and mean absolute deviation (MAD) were used to determine the fit model for making predicting. In this study, we found the best model as a GARCH (1,1) model.

Key words: *arch, garch, egarch, arima, volatility, forecasting, sugar price*

INTRODUCTION

Commodity prices has volatility over time and volatility may be defined for measuring the price varieties of financial data over time. Volatility can give a significant information when the volatility has a good interpretation. Especially, volatility is more sensitive in the financial markets than the other commodity markets. For instance, jewellery, oil, gas, agricultural commodity prices are linked with natural disasters, wars, economic crisis and unexpected meteorological conditions.

G20 Leaders Declaration at Los Cabos Summit emphasized The Action Plan on Food Price Volatility and Agriculture adopted by the Ministers of Agriculture in 2011 underlined that to feed a world population expected to exceed 9.3 billion by 2050, agricultural production will have to increase between 50 and 70 percent, and by almost 100 percent in developing countries (G20 Information Centre, 2020) [15].

G20 Leaders' Declaration at St. Petersburg Summit in 2013 they reaffirm their determination to implement all previous G20 commitments and existing initiatives including that stated in the Action Plan on Food Price Volatility and Agriculture which the G20 endorsed in 2011 G20 Information Centre, (2020) [16].

In these days, many researchers investigate the forecasting of agricultural commodity prices on different countries by using various approximations.

Aradhyula and Holt (1988) [3] applies recent developments in time-series modelling to analyse the retail prices of beef, pork, and chicken. Ex post forecast intervals generated from the GARCH processes indicate that the forecasting accuracy of the estimated models has varied widely over time with substantial volatility occurring during the 1970s and early.

Yang and Leatham (1999) examine the price discovery function for three U.S. wheat futures markets: the Chicago Board of Trade, Kansas City Board of Trade, and Minneapolis Grain Exchange [36].

Yang, Haigh, Leatham (2001) examine the effect of the recent radical agricultural liberalization policy, i.e. the 1996 FAIR Act, on agricultural commodity price volatility using GARCH models. Results of the study indicate that the agricultural liberalization policy has caused an increase in the price volatility for three major grain commodities (corn, soybeans and wheat) and little change for oats, but a decrease for cotton [37].

Apergis and Rezitis (2003) investigates volatility spillover effects across agricultural input prices, agricultural output prices and retail food prices using the technique of GARCH models. Their findings show that the volatility of both agricultural input and retail food prices exerts significant, positive spillover effects on the volatility of agricultural output prices [2].

Beckmann and Czudaj (2014) investigate the volatility spillover between various agricultural futures markets from a new perspective. Their study results provide evidence in favour of an existing short-run volatility transmission process in agricultural futures markets [5].

Zhang and Choudhry (2015) investigate the forecasting ability of six different generalized GARCH models; bivariate GARCH, BEKKGARCH, GARCH-X, BEKK-X, Q-GARCH and GARCH–GJR based on two different distributions (normal and student-t). Forecast errors based on four agricultural commodities' futures portfolio return forecasts (based on forecasted hedge ratio) are employed to evaluate the out-of-sample forecasting ability of the six GARCH models. The four commodities under investigation are two storable commodities: wheat and soybean, and two non-storable commodities: live cattle and live hogs [39].

Sanjuan-Lopez and Dawson (2017) examine the effects of speculation in the form of index trading on contemporaneous returns and volatility on corn, soybeans and wheat futures markets on the Chicago Board of Trade using multivariate generalised autoregressive conditional heteroscedasticity models and weekly data for 2006 –2014 [28].

In 2018, the crystal sugar production in Turkey was estimated to be 685,560 metric tonnes. The demand and supply of sugar relies on various factors such as domestic/foreign political implications, economic conditions, meteorological and environmental factors. Moreover, there is a high difference mark between the sugar beet at producer prices and crystal sugar at consumer prices (Turkseker, 2020) [30].

Sugar is a curious crop that due to the fact that it gives raw materials for agriculture sector. TURKSEKER beet sugar industry has 15 sugar factories that its capacity has 36% of its demand. TURKSEKER is a good and efficient organization in Turkey that it is responsible for the marketing and the production of sugar. The sugar price has been determined by the supply conditions in Turkey. Consumer prices has been steadily increasing for that reason it is very important part of economic events. Especially, household behavior in Turkey sensitive these prices and they follow all food prices in every time to buy the cheapest food for nutrition. The responsible organization in Turkey follow the sugar production and price to implementation for efficient and productive policy.

Time series analysis has been using in different areas for instance in econometrics, economics, social sciences and etc. In this paper, we aim to analyze the Turkish sugar price on a monthly base between 1994 and 2020 and ARCH, GARCH, EGARCH models and Box-Jenkins methods were used for forecasting the next years. The sugar price data was gathered from The Turkish Statistical Office's (Turkstat) database. (Turkstat, 2020) [31].

The study has four parts that first section is about the literature for sugar price. Second and third parts about the methodology of ARCH, GARCH, EGARCH and Box-Jenkins method. And, the last section has the empirical findings and discussions.

MATERIALS AND METHODS

Autoregressive Conditional Heteroskedasticity (ARCH), GARCH, EGARCH and ARIMA models particularly tested in this study. This study's contribution in literature is to determine the fit model for the sugar price data via comparing these methods.

Data

The Turkish sugar price data has about monthly data and it was taken from January 1st, 1994 to April 31st, 2020. Its number of observations is n=316. This data includes commodity price and gathered from the Turkish Statistical Institute (TurkStat) database.

Forecasting Methods

Forecasting research has been used increasingly in the world. Especially, GARCH, EGARCH, TARCH models and Box-Jenkins ARIMA model are popular methods for predicting analysis.

ARCH(Q) model

In order to test the financial series volatility, the Autoregressive Conditional Heteroscedasticity (ARCH) model was developed by Engle (1982) [14]. ARCH model has a conditional mean equation and a conditional variance equation. Before estimating GARCH models, it must test for autocorrelation of residual. After that, the variance equation has to be estimated during the process. Maximum likelihood method is used to estimation for the mean equation and the variance equation. ARCH model is an autoregressive process (AR) and written as:

The ARCH regression model is obtained by assuming that the mean of y_t is given as $x_t\beta$ a linear combination of lagged endogenous and exogenous variables included in the information set ψ_{t-1} with β a vector of unknown parameters.

Formally,

$$y_{t|}\psi_{t-1} \sim N(x_t\beta, h_t), \quad (1)$$

$$h_t = h(\varepsilon_{t-1}, \varepsilon_{t-2}, \dots, \varepsilon_{t-p}, \alpha) \quad (2)$$

$$\varepsilon_t = y_t - x_t\beta \quad (3)$$

The variance function can be further generalized to include current and lagged x's as these also enter the information set. The h function then becomes,

$$h_t = h(\varepsilon_{t-1}, \varepsilon_{t-2}, \dots, \varepsilon_{t-p}, x_t, x_{t-1}, x_{t-2}, \dots, x_{t-p}, \alpha) \quad (4)$$

or simply

$$h_t = h(\psi_{t-1}, \alpha) \quad (5)$$

σ^2 : the conditional variance of random variable.

$$\sigma_t^2 = var(u_t | u_{t-1}, u_{t-2}, \dots) = E[(u_t - E(u_t))^2 \, | u_{t-1}, u_{t-2}, \dots] \quad (6)$$

Since $E(u_t) = 0$, therefore

$$\sigma_t^2 = var(u_t | u_{t-1}, u_{t-2}, \dots) = E[u_t^2 \, | u_{t-1}, u_{t-2}, \dots] \quad (7)$$

The ARCH effect is modeled as;

$$\sigma_t^2 = \gamma_0 + \gamma_1 u_{t-1}^2 \quad (8)$$

$$var(u_t) = \gamma_0 + \gamma_1 u_{t-1}^2 \qquad u_t \sim N(0, var(u_t)) \quad (9)$$

γ_0, γ_1 are unknown parameters.

Full model is expressed as;

$$r_t = \mu + u_t, \qquad u_t \sim N(0, \sigma_t^2) \quad (10)$$

$$\sigma_t^2 = \gamma_0 + \gamma_1 u_{t-1}^2 \quad (11)$$

$$\gamma_0 \geq 0, \gamma_1 \geq 0 \quad (12)$$

i) a conditional variance its value must always be strictly positive.

$$r_t = \mu + u_t, \qquad u_t \sim N(0, \sigma_t^2) \quad (13)$$

$$\sigma_t^2 = \gamma_0 + \gamma_1 u_{t-1}^2 + \gamma_2 u_{t-2}^2 + \dots + \gamma_p u_{t-p}^2 \quad (14)$$

$$H_0: There\ is\ no\ ARCH\ effect \quad (15)$$

$$H_a: There\ is\ ARCH\ effect \quad (16)$$

If there is no serial correlation in the error variance, then

$$H_0: \gamma_1 = \gamma_2 = \dots = \gamma_p = 0 \quad (17)$$

$$\hat{u}_t^2 = \hat{\gamma}_0 + \hat{\gamma}_1 \hat{u}_{t-1}^2 + \hat{\gamma}_2 \hat{u}_{t-2}^2 + \dots + \hat{\gamma}_p \hat{u}_{t-p}^2 \quad (18)$$

GARCH models

The ARCH process introduced by Engle (1982) explicitly recognizes the difference between the unconditional and the conditional variance allowing the latter to change over time as a function of past errors (Bollerslev, 1986) [6].

The GARCH (p, q) process (Generalized Autoregressive Conditional Heteroskedasticity) is then given by,

$$\varepsilon_{t|}\psi_{t-1} \sim N(0, h_t), \quad (19)$$

$$h_t = \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{i=1}^{p} \beta_i h_{t-i} \quad (20)$$

$$\alpha_0 + A(L)\varepsilon_t^2 + B(L)h_t \quad (21)$$

where

$$p \geq 0, \quad q > 0 \quad (22)$$

$$\alpha_0 > 0, \quad \alpha_i \geq 0, \quad i = 1, \dots, q, \quad (23)$$

$$\beta_i \geq 0, \quad i = 1, \dots, p. \quad (24)$$

For p=0 the process reduces to the ARCH(q) process, and for p=q=0 ε_t is simply white noise. In the ARCH(q) process the conditional variance is specified as a linear function of past sample variances only, whereas the GARCH(p,q) process allows lagged conditional variances to enter as well.

The GARCH(p,q) regression model is obtained by letting the $\varepsilon_t's$ be innovations in a linear regression,

$$\varepsilon_t = y_t - x_t'b \quad (25)$$

where y_t is the dependent variable, x_t a vector of explanatory variables, and b a vector of unknown parameters (Bollerslev, 1986).

As pointed out by Sastry Pantula and an anonymous referee, an equivalent representation of the GARCH(p,q) process is given by

$$\varepsilon_t^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{p} \beta_j \varepsilon_{t-j}^2 - \sum_{j=1}^{p} \beta_j v_{t-j} + v_t \quad (26)$$

and

$$v_t = \varepsilon_t^2 - h_t = (\eta_t^2 - 1) h_t \quad (27)$$

where

$$\eta_t \overset{i.i.d.}{\sim} N(0,1) \quad (28)$$

The simplest but often very useful GARCH process is of course the GARCH(1,1) process given by (1) and

$$h_t = \alpha_0 \alpha_1 \varepsilon_{t-1}^2 + \beta_1 h_{t-1}, \qquad \alpha_0 > 0, \alpha_1 \geq 0, \beta_1 \geq 0 \quad (29)$$

$\alpha_1 + \beta_1 < 1$ suffices for wide-sense stationarity.

EGARCH model

Different models have been developed for testing the asymmetry of volatility. Developed by the EGARCH model by (Nelson, 1991) [24] can be written as:

$$\ln(\sigma_t^2) = \omega + \sum_{i=1}^{p} \alpha_i \left|\frac{\varepsilon_{t-i}}{\sigma_{t-i}}\right| + \sum_{j=1}^{q} \beta_j log \sigma_{t-j}^2 + \sum_{k=1}^{r} \gamma_k \frac{\varepsilon_{t-k}}{\sigma_{t-k}} \quad (30)$$

where

σ_t^2: the conditional variance,

$\omega, \alpha_i, \beta_j, and\ \gamma_k$ are parameters to be estimated.

In order to provide stationary, β_j parameter should be positive and < 1.

γ_k is an indicator of leverage effect that means asymmetry. This parameter must be negative and statistically significant (Dritsaki, 2018) [13].

The ARCH - GARCH Estimation

In the form of conditional heteroscedasticity, the model for the mean and variance [AR(1)-GARCH (1,1)] can be expressed as;

$$r_t = \mu + \varphi r_{t-1} + u_t, \qquad u_t \sim N(0, \sigma_t^2) \quad (31)$$

$$\sigma_t^2 = \gamma_0 + \gamma_1 u_{t-1}^2 + \lambda \sigma_{t-1}^2 \quad (32)$$

σ_t^2 is the variance of the errors.

The maximum likelihood method is used for the estimation of GARCH models. The logarithmic function of maximum likelihood is computed from the conditional densities of the prediction errors and is provided in the following form:

$$L = -\frac{1}{2} \sum_{t=1}^{n} [\ln(2\pi) + \ln(\sigma_t^2) + z_t^2] \quad (33)$$

where,

n: the number of observations,

σ_t^2: conditional variance,

$z_t^2 = \frac{\varepsilon_t^2}{\sigma_t^2}$,

$\varepsilon_t = r_t - \mu$,

r_t : the rate of return.

The Box-Jenkins Method

Forecasting is very important method to estimate the next periods that using in economics, business and industry. Holt (1957, 1963) [18] [19], Winters (1960) [33], Brown (1962) [9] and Coutie (1964) [10] used moving averages. The ARIMA abbreviation stands for autoregressive integrated moving average model. (Box and Jenkins 1976) [8] applied this methodology. ARIMA is used in time series analysis and forecasting in many studies. Such as (Yule 1927) [38], (Slutsky 1937) [29], (Walker 1931) [32], (Yaglom 1955) [35], (Libert 1984) [21], (Maberly 1986) [22], (Poulos et al. 1987) [26], (Bowerman and O'Connell 1987) [7], (Wu and Zhang 1997) [34], (Kim 2003) [20] and (Gooijer and Hyndman 2006) [17].

Evaluation of the models

MAE, MAPE, RMSE and MAD criteria are used during the forecasting to select the best model.

RMSE, MAPE and MAD statistics

There is some performance statistics such as MAPE, RMSE, MAE and MAD. MAPE were used by Alon et al. 2001 [1] and Ravindran and Warsing 2013 [27]. RMSE was stressed by Barnston 1992 [4]. Dritsaki 2018 used MSE, MAE, RMSE and MAPE.

$$MSE = \frac{\sum_{t=1}^{T} (r_t^2 - \sigma_t^2)^2}{T} \quad (34)$$

$$RMSE = \sqrt{\frac{\sum_{t=1}^{T} (r_t^2 - \sigma_t^2)^2}{T}} \quad (35)$$

$$MAPE = \frac{1}{T} \sum_{t=1}^{T} \left|\frac{r_t^2 - \sigma_t^2}{\sigma_t^2}\right| \quad (36)$$

$$MAE = \frac{1}{T} \sum_{t=1}^{T} |r_t^2 - \sigma_t^2| \quad (37)$$

In these formulas; t is time period, T is total number of observations, $y_t$is actual value, and $\hat{y}_t$ is forecasted value at time t. As a conclusion, if we have a small value for the prediction error, producing forecasted value from the model will be good.

RESULTS AND DISCUSSIONS

The data used on this model of sugar price are monthly and refer to rgprice.

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The data range is from January 1994 until April 2020. It is a total of 316 observations.

All data are gathered from Turkish Statistical Institute (TurkStat). The average monthly values of sugar price and their returns are given in Figures 1 and 2, respectively. Monthly percentage return of sugar price is the first difference from natural logarithm of sugar price and is given from the following equation:

$$R_t = 100 * \ln\left(\frac{X_t}{X_{t-1}}\right) = 100 * [\ln(X_t) - \ln(X_{t-1})] \quad (38)$$

where R_t is monthly percentage return to sugar price and X_t is sugar price at time t.

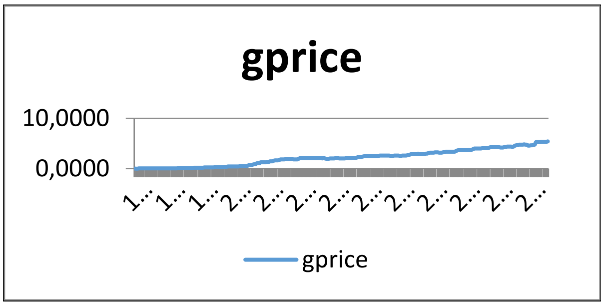

Fig. 1. Average monthly values of sugar prices
Source: Author's calculations.

We can see the nonstationary shape of the time series in the following graphics. This series is going to be examined.

This series is randomly fluctuating and indicating the observation of a global trend. In particular, after the year 2001, the time series quickly increases, and then the prices show the behavior of uptrend. Average monthly values of sugar prices are present a random walk (Figure 1).

Average monthly values of sugar prices rate are steady from Fig. 2. Thus, we can see the variance are unstable that sugar price returns show volatility.

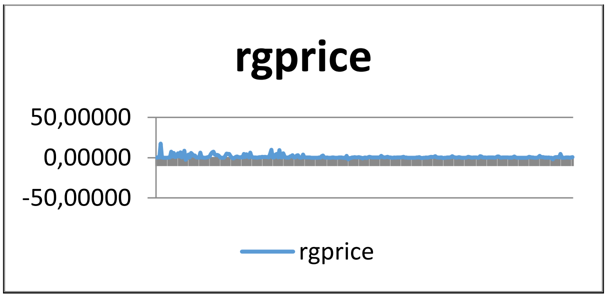

Fig. 2. Average monthly values of return of sugar prices
Source: Author's calculations.

Table 1 presents the correlograms, and we will test if there is autocorrelation on average monthly returns of sugar price, as well as the ARCH effect. This result, belong to Bollerslev (1986), features GARCH models as the most suitable for the data of sugar price rate.

Table 1. Correlogram of average monthly return of sugar price

Date: 06/23/20 Time: 19:04
Sample (adjusted): 1994M02 2020M04
Included observations: 315 after adjustments

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.474	-0.474	71.597	0.000
		2	-0.051	-0.356	72.415	0.000
		3	0.132	-0.102	78.002	0.000
		4	-0.167	-0.219	86.910	0.000
		5	0.084	-0.128	89.204	0.000
		6	-0.015	-0.126	89.279	0.000
		7	-0.079	-0.197	91.324	0.000
		8	0.112	-0.101	95.420	0.000
		9	-0.105	-0.195	99.038	0.000
		10	0.162	0.039	107.65	0.000
		11	-0.123	-0.086	112.63	0.000
		12	-0.046	-0.156	113.34	0.000
		13	0.141	-0.057	119.92	0.000
		14	-0.152	-0.165	127.60	0.000
		15	0.140	-0.012	134.08	0.000
		16	-0.025	-0.023	134.29	0.000
		17	-0.085	-0.047	136.71	0.000
		18	0.151	0.055	144.42	0.000
		19	-0.137	-0.018	150.75	0.000
		20	0.016	-0.043	150.84	0.000
		21	0.014	-0.091	150.90	0.000
		22	0.011	0.031	150.94	0.000
		23	-0.019	-0.086	151.06	0.000
		24	-0.013	-0.083	151.12	0.000
		25	0.067	-0.023	152.67	0.000
		26	-0.022	-0.023	152.84	0.000
		27	0.012	0.082	152.89	0.000
		28	-0.010	-0.004	152.92	0.000
		29	-0.073	-0.037	154.80	0.000
		30	0.121	0.082	159.96	0.000
		31	-0.090	-0.017	162.83	0.000
		32	0.026	0.041	163.06	0.000
		33	0.013	0.003	163.12	0.000
		34	-0.036	0.026	163.57	0.000
		35	0.047	0.020	164.34	0.000
		36	-0.030	0.013	164.67	0.000

Source: Author's calculations.

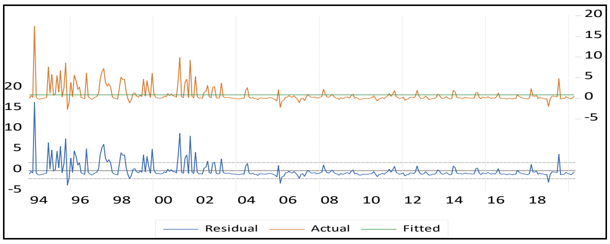

Fig. 3. Residual of sugar price
Source: Author's calculations.

The one step in the process was to create a time series plot of the data, which displayed the average monthly sugar prices for each year for the monthly from 1994 to 2020. The results of Figure 4 show that average monthly returns of the sugar price follow the normal distribution. Also, asymmetry's coefficient that is skewness shows that the distribution of sugar price returns is right asymmetric (3.666), is leptokurtic (k=22.859), and has heavy tails (Fig.4).

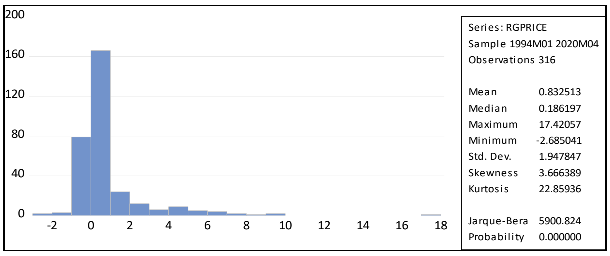

Fig. 4. Descriptive statistics and normal density graphs of average monthly return on the sugar price
Source: Author's calculations.

We test the stationarity of the average monthly returns of the sugar price using Dickey-Fuller (1979, 1981) [11] [12] and Phillips Perron (1998) [25] tests. The results in Table 2 show that the average monthly returns of the sugar price are stationary in their levels on both used tests.

Table 2. Stationarity test of average monthly returns of the sugar price

Variable	ADF		P-P	
	Constant	Constant, Trend	Constant	Constant, Trend
RGPRICE	-7.289341 (2)*	-9.321505 (3)*	-15.48088 (9)*	-16.27060 (3)*

Notes: * denotes the significant at 1%, 5% and 10% levels, significantly. The numbers in parentheses represent the lag length.
Source: Author's calculations.

ARIMA model selection for the sugar prices of Turkey

Akaike's Information Criterion (AIC) is expressed below the formula:

$$AIC = log\hat{\sigma}^2 + 2\frac{p+q}{n} \quad (39)$$

Schwarz (SBC) or Bayesian Information Criterion (BIC) is expressed below the formula:

$$BIC = log\hat{\sigma}^2 + 2\frac{p+q}{n}\log(n) \quad (40)$$

To determine the best values for the model, we use and prefer the smallest AIC or BIC values. According to literature, these two criteria are differ for some properties and the BIC criterion is preferred. Because, it has the feature that it will almost surely select the true model.

And, different ARIMA (p,d,q) results showed in Table 3. In addition to, the optimum lag length and information criterion for the ARIMA (p,d,q) for D(RGPRICE) are presented in Table 3. With respect to LogL, Akaike (AIC), Schwartz (BIC), and Hannan-Quinn (HQ) criteria, ARIMA (3,0,3) model is the most suitable as far as the mean monthly returns for the sugar price are related (Table 3).

The information criteria favor the ARIMA (3,0,3) and its results are given below in Table 4.

Table 3. LogL, AIC*, BIC and HQ test results

Model Selection Criteria Table				
Dependent Variable: D(RGPRICE)				
Model	LogL	AIC*	BIC	HQ
(3,3)(0,0)	***-620.012689***	***3.987382***	***4.082686***	***4.025459***
(2,4)(0,0)	-620.120545	3.988067	4.083370	4.026144
(2,3)(0,0)	-621.783439	3.992276	4.075666	4.025593
(4,4)(0,0)	-619.297530	3.995540	4.114669	4.043137
(4,3)(0,0)	-621.397972	4.002527	4.109743	4.045364
(3,4)(0,0)	-621.673105	4.004274	4.111490	4.047111
(4,1)(0,0)	-631.729735	4.055427	4.138817	4.088745
(0,1)(0,0)	-635.791281	4.055818	4.091556	4.070097
(0,2)(0,0)	-635.381235	4.059563	4.107215	4.078602
(1,1)(0,0)	-635.381877	4.059567	4.107219	4.078606
(4,2)(0,0)	-631.587745	4.060875	4.156178	4.098952
(1,2)(0,0)	-634.738072	4.061829	4.121394	4.085627
(0,3)(0,0)	-635.379622	4.065902	4.125467	4.089701
(2,1)(0,0)	-635.381741	4.065916	4.125480	4.089714
(3,2)(0,0)	-633.556603	4.067026	4.150417	4.100344
(0,4)(0,0)	-634.602716	4.067319	4.138796	4.095877
(1,4)(0,0)	-633.715826	4.068037	4.151427	4.101355
(2,2)(0,0)	-634.719235	4.068059	4.139536	4.096617
(1,3)(0,0)	-634.723258	4.068084	4.139562	4.096642
(3,1)(0,0)	-634.966204	4.069627	4.141104	4.098185
(4,0)(0,0)	-657.030081	4.209715	4.281192	4.238273
(3,0)(0,0)	-666.729964	4.264952	4.324517	4.288750
(2,0)(0,0)	-669.025698	4.273179	4.320831	4.292218
(1,0)(0,0)	-690.248183	4.401576	4.437315	4.415855
(0,0)(0,0)	-730.309610	4.649585	4.673411	4.659104

Source: Author's calculations.

Table 4. Estimation of ARIMA(3,0,3) model

Dependent Variable: D(RGPRICE)				
Method: ARMA Maximum Likelihood (BFGS)				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.007085	0.005518	-1.283910	0.2001
AR(1)	-1.485977	0.051148	-29.05273	0.0000
AR(2)	-0.811079	0.077487	-10.46731	0.0000
AR(3)	0.112004	0.048576	2.305742	0.0218
MA(1)	0.679851	18.89401	0.035982	0.9713
MA(2)	-0.601398	16.47642	-0.036501	0.9709
MA(3)	-0.970395	54.72022	-0.017734	0.9859
SIGMASQ	2.900088	29.64561	0.097825	0.9221
R-squared	0.520144	Mean dependent var		0.001875
Adjusted R-squared	0.509202	S.D. dependent var		2.462297
S.E. of regression	1.725010	Akaike info criterion		3.987382
Sum squared resid	913.5277	Schwarz criterion		4.082686
Log likelihood	-620.0127	Hannan-Quinn criter.		4.025459
F-statistic	47.53923	Durbin-Watson stat		2.015530
Prob(F-statistic)	0.000000			
Inverted AR Roots	.11	-.80+.59i	-.80-.59i	
Inverted MA Roots	.97	-.83-.56i	-.83+.56i	

Source: Author's calculations.

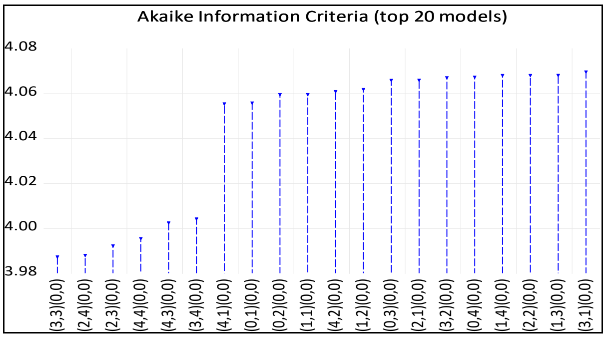

Fig. 5. Akaike Information Criteria results
Source: Author's calculations.

Empirical Results

We found the Prob. Chi-Square = 0.0084 < 0.05. And, refer to the hypothesis, we can't accept the null hypothesis. Namely, we accept the alternative hypothesis that there is ARCH effect. We can conclude that we can run the ARCH family models such as GARCH, EGARCH and so on.

$$H_0: There\ is\ no\ ARCH\ effect$$
$$H_a: There\ is\ ARCH\ effect$$

If we start to estimate ARCH(q), GARCH(p,q) and EGARCH(p,q) models, we can look into ARCH effects on the returns of the sugar price. Marquardt's algorithm (1963) [23] is used for the estimation of the parameters.

Some statistics belong to the estimated models are given in Table 5. We can look the log-likelihood (LL) value for fitting the model. If LL value has a high value, we can say that LL gives a good fit value.

The estimations of all models and the standard errors of the parameters (coefficients) together with the value of log-likelihood function, as well as the normality test, autocorrelation test, and conditional heteroscedasticity test in Table 5.

If we decide the most suitable value, we can look some statistics such as significance of coefficients, LL value, autocorrelation and heteroscedasticity. In here, The ARIMA(3,0,3)-GARCH(1,1) model for GED is the fitted distribution according to these statistics. In this model, whole coefficients are significant at 5% level, LL value has the highest value, no autocorrelation and heteroscedasticity. As a conclusion, this model is fitted for predicting (Table 5).

Table 5. ARIMA(3,0,3)-ARCH(1), ARIMA(3,0,3)-GARCH(1,1), and ARIMA(3,0,3)-EARCH(1,1) results

ARIMA (3,0,3)-ARCH(1)			
Parameter	Normal	t-Student	GED
ω	3.220(0.000)	376.63(0.999)	1.166(0.000)
α_1	0.217(0.000)	2415.93(0.999)	3.978(0.062)
		DOF=2.000(0.000)	GED=0.373(0.000)
Log-likelihood	-654.38	-403.93	**-389.60**
ARIMA (3,0,3)-GARCH(1,1)			
ω	0.016(0.000)	181.14(0.998)	0.008(0.000)
α_1	0.053(0.000)	1107.68(0.998)	-0.013(0.088)
β_1	0.924(0.000)	0.009(0.003)	0.989(0.000)
		DOF=2.000(0.000)	GED=0.4900(0.000)
Log-likelihood	-512.06	-402.38	**-373.82**
ARIMA (3,0,3)-EGARCH(1,1)			
ω	-0.117(0.000)	-0.128(0.003)	-0.003(0.889)
α_1	0.161(0.000)	1.365(0.036)	0.071(0.278)
β_1	-0.223(0.000)	-0.643(0.131)	-0.157(0.005)
γ_1	1.035(0.000)	1.000(0.000)	1.066(0.000)
		DOF=2.011(0.000)	GED=0.464(0.000)
Log-likelihood	-500.64	-403.41	**-373.30**
Notes: Value in parentheses denotes the p-values			

Source: Author's calculations.

ARIMA(3,0,3)-EGARCH(1,1) model with the GED distribution isn't good for forecasting. Because, coefficients are not significant, β_1 coefficient is negative and less than 1 indicating that the stationarity of the model. Moreover, γ_1 coefficient is positive and not significant statistically that showing the stationarity of the model. As a result, we can't use this model for predicting (Table 5).

Forecasting

At this point, for the predicting of ARIMA(3,0,3)-GARCH(1,1) model on the returns of sugar price, dynamic and static procedures are used. During the dynamic estimation, the lags of dependent variable and ARMA terms are used for estimation. That is, this procedure is implemented by n-step ahead forecasting. The other procedure is static. In this step, we use the actual values belong to dependent variable. Its name of procedure is one-step ahead forecast. Using the dynamic and static forecast, the evaluation of forecasting the returns of sugar price is implemented and presented, respectively in Figure 5.

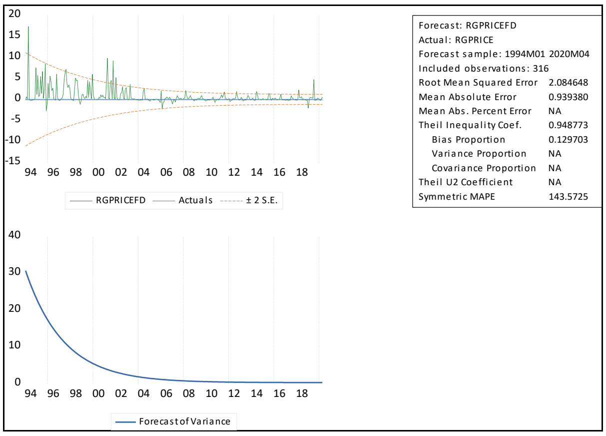

Fig. 6. Dynamic forecast of sugar price (GARCH)
Source: Author's calculations.

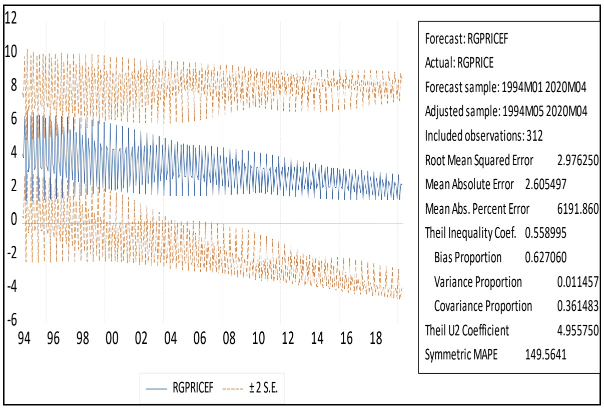

Fig. 7. Dynamic forecast of sugar price (ARIMA)
Source: Author's calculations.

Especially, some indicators are given in here for intance the determined model is complying with the past data, the fitted values link with the scatter of the actual data are good. There are some indicators such as the RMSE, MAE and MAPE are low relative to other models, the adjusted R^2 is high. As a conclusion, residuals are white noise (Table 6).

Table 6. The test accuracies of the forecasting m GARCH and ARIMA methods for sugar prices

Methods	The criteria		
	RMSE	**MAPE**	**MAE**
GARCH	2.085*	NA*	0.939*
ARIMA	2.976	6191.86	2.605
GARCH is the best model for making forecasts			

Source: Author's calculations.

CONCLUSIONS

This paper emphasizes on the creative of a model for the Turkish sugar price. When sugar price can give volatility, GARCH models are convenience for using as a model. Moreover, ARIMA(3,0,3)-ARCH(1), ARIMA(3,0,3)-GARCH(1,1) and ARIMA(3,0,3)-EGARCH(1,1) models were estimated for registering symmetry effect's volatility on sugar price. The estimation of ARIMA(3,0,3)-EGARCH(1,1) model is used for finding the leverage effect. That is, positive shocks cause for the lower volatility. As a conclusion, By using the dynamic process, ARIMA(3,0,3)-GARCH(1,1) model is gathered. According to results of this study, we can say that GARCH model has a good estimation to predict the sugar prices.

In order to identify the ARIMA model for a time series, we calculated the different ARIMA models. In this study, first of all sugar prices are taken by logarithmized and used the first order difference. This method is the best way to select the ARIMA model.

During the evaluation, important statistical tests were used. Especially, the significance of the coefficients and used to test the residuals were taken. To evaluate the fit of the ARIMA models, The Akaike information criterion (AIC) and the Bayes information criterion (BIC) are used. The R^2 and Adjusted R^2 were evaluated. In order to determine the best ARIMA model, these criteria are used. The autocorrelation and partial autocorrelation give the impression that the residuals estimated from the ARIMA (3,0,3) are approximately white noise. The mean absolute percentage error (MAPE), root mean square error (RMSE) and mean absolute deviation (MAD) are used for selecting the best model forecasting.

Due to all criteria values for the GARCH (1,1) model are the lowest and fitted values is the best model in this study by comparing these criteria.

We believe that the research methodology and the results given in this paper can be useful for the strategy setting of Turkish agricultural economists, economists and government authorities.

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